Keeping the Car Clean:

On the Electrification of Private Transport

PhD Thesis

James Dixon

EPSRC Centre for Doctoral Training in Future Power Networks and Smart Grids
Department of Electronic & Electrical Engineering
University of Strathclyde, Glasgow

April 21, 2020

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed:

Date:

Abstract

The electrification of private road vehicles – and the provision of a low carbon generation mix that supplies the energy for their motion – is likely to be a key contributor to meeting *net zero* targets and limiting the disastrous effects of anthropogenic climate change.

The work presented in this thesis surrounds two aspects of this transition. Firstly, as EVs are fundamentally different to internal combustion vehicles (ICVs), in that their energy storage capacity is far smaller and the rate at which it can be replenished is much slower, there has been consumer resistance to their adoption due to the perception that their charging carries inconvenience compared to ICV fuelling. Secondly, as the energy demand of private road vehicles is shifted from the petrochemical supply chain to the electricity grid, there are potential i) issues surrounding the resilience of the grid and ii) opportunities resulting from the flexibility and 'schedulability' of EV charging in enabling the further decarbonisation of the power sector.

With regards to the first aspect, this thesis presents an investigation of the inconvenience of EV charging versus ICV fuelling and how this is likely to change depending on vehicle parameters – battery capacity and charger power – and the set of locations at which it can be charged. It was found that if the EV can be charged while parked at home, the majority (80-95%) of individuals could make the transition to EVs without suffering any increase in time penalty associated with charging compared to ICV fuelling with modest battery capacities at the lower end of the market. However, for drivers who cannot charge at home this *convenience parity* is harder to achieve.

This can be made easier by increasing battery capacity and charger power and ensuring the provision of public destination and en route charging infrastructure. This thesis presents characterisation of the likely demand at such infrastructure based on the analysis of smartphone app users' locational data. It was found that this kind of EV charging demand is likely to vary significantly in time and by location, depending on what kind of public amenity it is installed at; such an approach could be invaluable to transport and power system planners given the projected rapid uptake of EVs.

This thesis presents analysis into the likely impact of EV charging on residential distribution networks, taking into account the effect of i) the way in which drivers schedule charge events, ii) the social demographics (and hence travel habits) of the individuals served by a network and iii) the effect of the rapidly evolving EV sector and the resulting changes in technical parameters and level of charging infrastructure. By means of case studies on real distribution networks in Glasgow's Southside, it was found that all three of the above factors have a significant effect on the impact seen from EV charging and that, if their charging is uncontrolled, residential distribution networks in better-off areas with high rates of car ownership are unlikely to be able to cope with charging load when over 40% of vehicles are replaced with EVs.

Based on the above finding, this thesis presents an investigation of the potential of EVs to interact positively with the grid, by charging selectively to i) avoid network peaks and thus enable a higher penetration of EVs before the network must be reinforced and ii) enable the further decarbonisation of the power system by charging when grid carbon emissions are low and local renewable energy is in surplus. Techniques to schedule charge events are presented: a 'valley filling' optimisation approach based on the controller having perfect foresight of the arrival of vehicles to represent the best case; and a set of low-information heuristics that could operate using data from 'smart' EV chargers. Though some of the heuristics could perform similarly to the formal optimisation, both methods resulted in the network being operated outwith statutory GB voltage limits for 100% penetration of EVs. Finally, it was found that there is significant potential for EVs to complement the decarbonisation of the power system. If 'smart charged', their resulting carbon intensity (gCO_2/km) can be reduced to around a fifth of that of a new petrol or diesel car if charged from the current GB grid. Furthermore, a penetration of 20% EVs in Scotland could be smart-charged to absorb up to 75% of curtailed generation at Scotland's largest onshore wind farm.

Contents

List of Figures

List of Tables

Prologue/Acknowledgements

Pace of Change

This PhD began in October 2016. The year before, 195 United Nations Framework Convention on Climate Change member states signed the 2015 Paris Agreement [1], committing to keep global temperatures 'well below' 2°C above pre-industrial levels and to pursue efforts to limit the increase to 1.5°C, in recognition that this would substantially reduce the risks and impacts of climate change. Between then and the time of writing – three years later in October 2019 – there have been so many events shaping policy, public opinion and technology in such a short window of time that some writing to address this pace of change became a necessary point from which to start.

A matter of weeks after the start of this PhD saw a change of United States presidency, and a subsequent pledge to withdraw the US – the world's second largest greenhouse gas emitter – from the agreement (though the earliest possible withdrawal date is the 4$^{\text{th}}$ November 2020, one day after the 2020 presidential election). On the same day that the announcement was made, the United States Climate Alliance was formed between 24 states, comprising 50% of the country's population, to continue to advance the objectives of the Paris Agreement at the state level despite the federal withdrawal [2]. The overwhelmingly negative reaction to the US withdrawal from the international community [3, 4] sets the tone of the global mainstream attitude to climate change and the urgent need for radical change in how we produce and consume – or more properly, change the form of – energy.

In addition to mounting concern over climate change, fears over bad air quality have risen – contributed to by the revelation of the 2015-present 'Dieselgate' emissions scandal [5]. In 2017, the World Health Organization predicted that 90% of the world's population are living under air quality that does not meet their own legal requirements for safety [6], and that up to 70% of the most harmful particulate emissions are caused by road transport [7]. In July of the same year, the UK Government committed to a ban on all petrol and diesel car sales from 2040 [8], which followed similar announcements in France [9] and Norway [10]. Shortly afterwards, the Scottish Government committed to 'phase out' conventional vehicles by 2032 [11] and later in that same year more countries – including Ireland [12], Denmark [13] and the Netherlands [14] – committed to a ban from 2030. In 2018, the UK Department for Transport released their *The Road to Zero* report, addressing how policy intends to achieve the ban of new petrol and diesel cars by 2040, with more detailed interim targets, such as up to 70% of new cars having zero tailpipe emissions by 2030 [15].

In their 2018 *Special Report* [16], the Intergovernmental Panel on Climate Change (IPCC) published that, with high confidence, reaching and sustaining *net zero* global anthropogenic CO_2 emissions would halt anthropogenic global warming on multi-decadal time scales. In response, the Committee on Climate Change (CCC) – the independent advisory body to the UK Government on tackling and preparing for climate change – published their *Net Zero* report [17] in May 2019, which makes recommendations to UK Government on how vigorously to pursue targets on decarbonisation across all sectors in order to reach *net zero* emissions by 2050. As part of this report, the CCC state that all new cars and vans sold in the UK should be electric by 2035 at the latest, with cost savings projected as a result of an earlier switch.

Aside from shifts in international policy, a widespread change in societal attitudes to climate change, energy and the environment has fuelled this pace of change further. Increasing media coverage such as Sir David Attenborough's 2018 *Blue Planet II* series [18] are cited as a contributing factor of increasing public awareness of these issues. By starting the *Skolstrejk för klimatet* (School strike for climate), Greta Thunberg has inspired school children and people of all ages across the world to protest in the name of increased political action against the threat of climate change; the largest coordinated public protest ever recorded took place on 20$^{\text{th}}$ September 2019, with an estimated four million people marching in one day. As of 24$^{\text{th}}$ September, a mainstream UK political party has committed to *net zero* targets for 2030 [19]. To be in such a position was surely unthinkable at the time this PhD began.

This thesis, while rooted in the scope of electrified personal vehicles and the impact they may have on the electricity network and the individuals that drive them, is intended to serve as a reflection of the intent of engineers and scientific researchers of the time. It is, to quote a plaque addressed to future generations on the former *Okjökull*, the first of Iceland's glaciers to be lost to climate change, 'to acknowledge that we know what is happening and what needs to be done. Only you know if we did it.'

Acknowledgements

First of all to Keith Bell, for his thoughtful advice during my PhD and a near-constant barrage of great career opportunities and jazz recommendations. To Shirley Kirk, for making PhD life run so smoothly. To Waqquas Bukhsh, Ian Elders, Alan Collinson and Ciaran Higgins for all their help.

To Peter Bach Andersen and Chresten Træholt at DTU for their hospitality and supervision during my stay. Also to those who made my time in Copenhagen unforgettable, especially Judith Suter, for the painting and poetry; and Saga Úlfarsdóttir & Fannar Kristmannsson, for taking me swimming in the sea when it was minus three.

To all that have cemented Glasgow, in my head, as official number one place in the universe. Particularly Anthony Florida-James, for the storytelling; Lesiba Mokgonyana, for getting me lost in music; Marianne Gallagher, for bestowing me the title of South Yorkshire's ambassador to Glasgow; Rob Hamilton, for keeping it formal on two wheels; Jonathan Bowes, for the relentless enthusiasm of things; and Sofia Koukoura, for understanding that I don't realise how loud I sing in the shower.

To my family and friends *doon Sooth* that took long and costly trains to visit. Special mentions to premier sensei Sam Rooney, for the lunchtime Skypes from Tokyo; number one bear Dan Holden, for the hazy memories; and of course to Mum, Dad, Isabel and Emma for their unwavering support.

To Sara Hosseinzadeh, for whom I wouldn't have arrived in this magical city or done any of this otherwise, and without whom it wouldn't have been any good.

Nomenclature

Abbreviations

API	Application programming interface
AVR	Automatic voltage regulator
BM	Balancing Mechanism
CC	Constant current
CCC	Committee on Climate Change
CDF	Cumulative distribution function
CP	Convex programming
CV	Constant voltage
DNO	Distribution network operator
ESO	Electricity System Operator
EV	Electric vehicle
FCFS	First come first served
GIS	Geographical information system
ICV	Internal combustion vehicle
IPCC	Intergovernmental Panel on Climate Change

LP Linear programming

LRFS Lowest range first served

MC Monte Carlo

MEA My Electric Avenue

MILP Mixed integer linear programming problem

NHTS National Household Travel Survey

NTS National Travel Survey

OA Output Area

OLTC On-load tap changer

OPF Optimal power flow

PDF Probability density function

PV Photovoltaic

RES Renewable energy sources

SIMD Scottish Index of Multiple Deprivations

SoC State of charge

TUS Time Use Survey

V2G Vehicle to grid

VoLL Value of Lost Load

Sets

$\mathbb{N}$ Set of natural numbers

$\mathcal{B}$ Set of busbars, indexed by b

$\mathcal{C}$ Set of cars parked in car park, indexed by c

$\mathcal{D}$ Set of domestic demands, indexed by d

$\mathcal{E}$ Set of charge events, indexed by e

$\mathcal{G}$ Set of grid supply points, indexed by g

$\mathcal{I}$ Set of trips in UK National Travel Survey travel diary, indexed by i

$\mathcal{K}$ Set of trips in UK National Travel Survey travel diary that end with a potential parked charging event, indexed by k

$\mathcal{L}$ Set of lines, indexed by l

$\mathcal{S}$ Set of potential battery state of charge increases from possible parked charging events (subset of $\mathcal{K}$) before trip i

$\mathcal{T}$ Time horizon, indexed by t

$\mathcal{V}$ Set of electric vehicles, indexed by v

Variables

α,β Shape parameters for Beta distribution

$\bar{v}$ Average speed of trip

ΔE Energy delivered during charge event

ΔE^T,ΔE^{LHS},ΔE^{RHS} Energy delivered during charge event

Δ^{EV},$\hat{\Delta}^{EV}$ Total charging time penalty, total charging time penalty normalised by driving time

δ^e,δ^{fe},δ^c Total charging time penalty for en route charging events during a trip, fixed time penalty associated with plugging in/removing cable for en route charging events during a trip, time penalty associated with waiting for vehicle to charge for en route charging events during a trip

δ^{fuel} Fixed time penalty associated with fuelling

Δ^{ICV},$\hat{\Delta}^{ICV}$ Total fuelling time penalty, total fuelling time penalty normalised by driving time

δ^{p},δ^{fp} Total charging time penalty for parked charging event, fixed charging time penalty due to plugging in/removing cable for parked charging event

ϵ,ϵ^{c} Fuel economy of trip, combined driving cycle fuel economy value

η One-way efficiency of AC/DC converter for parked charging events

Γ Cost of carbon dioxide emissions

λ Decay constant for lithium ion charging curve during constant voltage region for parked charging event

Λ, Ω Variables for calculation of charging time from energy transfer

μ,$\bar{\mu}$ Arrival rate of vehicles to charging forecourt/petrol station, Average arrival rate of vehicles to charging forecourt/petrol station

Φ^{CC}, Φ^{CV},Φ^{CC-CV} Increase in state of charge from constant current parked charging event, increase in state of charge from constant voltage parked charging event, increase in state of charge from parked charging event with both constant current and constant voltage regions

Φ^{p}, Φ^{e} Increase in state of charge from parked charging event, increase in state of charge from en route charging events during a trip

Π Decision variable {0,1} to denote whether parked charging action taken; 0 if no parked charging action taken, 1 if parked charging action taken

σ^{s}, σ^{d} Battery state of charge on arrival, battery state of charge on departure

Θ, Ψ, ψ Total energy requirement of all vehicles in car park, potential charge rate of vehicles in car park, charge rate of vehicles in car park

ε Remaining energy required for trips up to the next parked charging opportunity (or the end of the travel diary), including that of the current trip

B Line susceptance

C Battery capacity

c,c^c Energy consumption of trip, combined driving cycle energy consumption value

c^G Grid carbon intensity

D Duration of trip

d Distance of trip

F Vector containing possible increases in state of charge following potential parked charging events

f,f^{min} Fuel requirement of trip, minimum permissible fuel

h Hours of driving before 15 minute break is mandated

N Charging forecourt/petrol station occupancy

n Number of en route charging stops necessary on trip

N_c Number of cars in charging queue

P^{DC},P^{AC} Maximum rated DC charging power available during parked charging event, Maximum rated AC charging power available during parked charging event

P^e DC charging power available during en route charging events

p^E,p^G,p^D,p^L Active power drawn by EV, active power contribution from grid supply point, active power drawn by domestic demand, active power flow on line

P^G, P^C, P^B, P^{EV} Available grid capacity, converter capacity, battery charging capacity, EV charging capacity

Q Local variable in parked charging scheduling algorithm used to track improvements to the state of charge by taking parked charging events

r^{min} Minimum permissible remaining range of vehicle

s Time spacing between vehicles in charging queue

S,S^{min} Battery state of charge including the addition due to any associated charging during or after the trip, minimum permissible state of charge

S^{DC} Line rating

T Average service time for charging forecourt/petrol station

t Time during charge event

t^{γ},t^{∞} Time at which vehicle reaches state of charge of γ in parked charging event, time at which the charging power reaches a value close to zero (taken as 1% of the maximum rated power) in parked charging event

t^{min} Minimum of t^{d} and t^{∞}

t^{s},t^{d} Time at which vehicle starts parked charging event, time at which vehicle departs parked charging event

V Volume of fuel tank

V^{D},V^{E} Value of lost load – domestic, value of lost load – EV charging

W Energy demand for trip

Z State of charge not including the addition due to any associated charging during or after the trip

P^{D},P^{E},P^{UB} Active power demand from domestic load, active power demand from EV charging, active power upper bound from wind farm

Nomenclature

Chapter 1

Introduction

1.1 Motivation

The transport sector made up a quarter – eight billion tonnes – of total worldwide CO_2 emissions in 2016, over three quarters of which were from road transport [20]. It is estimated that seven million people worldwide die every year from exposure to bad air quality, the majority of which is caused by road transport [6]. The electrification of private transport, combined with the continued decarbonisation of the generation mix that supplies the energy for their motion, represents one potential solution to these problems. Furthermore, the inherent underutilisation of the private car – in the UK, the average car spends 96% of its time parked [21] – means that electric vehicle (EV) charging is flexible compared with most domestic uses of electricity. This flexibility has the potential to assist in the further decarbonisation of the power sector. Firstly, by shifting charging demand to times when generation from intermittent renewable energy sources (RES, such as wind and solar) is in surplus, EV charging has the potential to increase the utilisation – and market value – of these generators. Secondly, by providing ancillary services to the grid, EV charging can help mitigate some of the problems posed to power system stability that arise from high RES penetration[1].

In their *The Road to Zero* publication [15], the UK Government stated that they expect the majority of EV charging to take place at peoples' homes, presenting policy

[1]This is further explained in Section 1.4.

support for grants to encourage the take-up of home chargers. However, concerns have been raised by electricity network owners [22], regulators [23] and policymakers [24,25] about the impact of widespread EV charging on residential distribution networks, where the capacity may not be able to cope with the increase in demand. The extent and timing of the need for intervention in these networks – whether traditional reinforcement or application of 'smart grid' technologies – is highly uncertain.

While the focus has been on people charging their vehicles at home, there has been only limited attention paid to individuals who may lack access to charging at home[2]. According to a Department for Transport survey [26], this applies to 43% of UK households. This proportion increases in urban areas: in Glasgow, 73% of dwellings are flats [27] – the majority of which have nowhere to park a car. While some of this charging demand could be met with on-street charging facilities, such as using lampposts to support EV chargers [28], it is unknown if this will be sufficient to meet the charging demand of up to 35 million EVs across Britain by 2040 as per National Grid's 2019 *Future Energy Scenarios* [29]. Due to fundamental differences between EVs and internal combustion vehicles (ICVs), lack of charging access is expected to have a significant effect on the use of electric vehicles, namely the time penalty associated with charging them. As this perceived convenience of EVs has a considerable effect on consumers' willingness to make the switch to EVs, this is an important subject to explore. Where those people will charge their vehicles is another cause for concern: if public destination, workplace and 'forecourt' style EV charging stations are to be widespread, planning for this new demand (which is expected to be different from the demand seen by residential charging) is necessary.

The motivation for the work presented in this thesis is that the electrification of private transport is, at the time of writing, cited as a key part of the radical changes required to meet *net zero* carbon emissions and mitigate the impacts of climate change and air pollution. The challenges, both to the individuals that would be EV drivers and the power system that provides their charging, must be quantified so that they can be

[2]There are further issues surrounding how the necessary network upgrades, and any financial revenue for EVs providing grid services, are funded if the only benefactors of those upgrades and/or payments are the owners of the vehicles. This is further discussed in the Epilogue.

addressed subject to the near and concrete deadlines involved [16] at minimal cost. The opportunities presented by the electrification of transport and by the set of technologies conceptually referred to as the 'smart grid' to both overcome these challenges and aid the further decarbonisation of the energy sector must be investigated.

1.2 The Electric Vehicle

1.2.1 Past and Present

In this thesis, an EV refers to a passenger car powered exclusively by chemical energy stored in a rechargeable battery pack. Excluded from analysis in this thesis are the following types of vehicle, which are also known as electric vehicles: plug-in hybrid electric vehicles, hydrogen fuel cell powered vehicles, electric bicycles/motorcycles and electric buses.

Although interest surrounding EVs has risen sharply in recent years, they are not new: some of the most popular vehicles in the late 19^{th} and early 20^{th} centuries were battery-powered electric vehicles [30]. However, the dominance of the internal combustion engine from the 1920s to the present day has limited the development of EV technology. Interest in EVs continues to rise sharply around the world, due to global concerns around greenhouse gas emissions, dependence on fossil fuels and air pollution, as previously discussed.

Figure 1.1 shows an example of an early EV (the French-made Krieger electric laudaulet in 1906) [30] and an example of a modern EV (the Volkswagen ID.3 EV, to be released in 2020) [31].

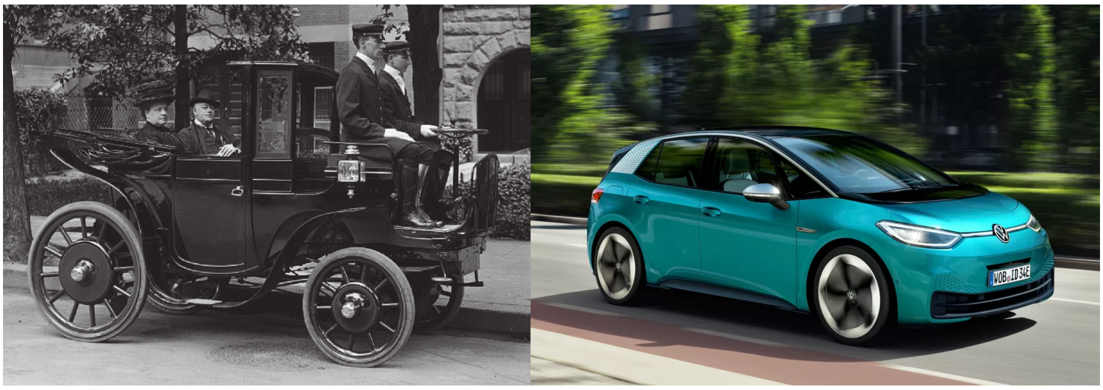

Figure 1.1: Krieger electric laudaulet in Washington D.C., 1906 (left); Volkswagen ID.3, to be released in 2020 (right)

2018 saw a doubling of the number of new EV registrations (either pure battery or plug-in hybrid) versus the previous year, with 2 million new EV registrations bringing the global electric fleet to 5.1 million [32]. Figure 1.2, reproduced from [32], shows that China is the world's largest EV market – with around 45% of the total – and Norway has the highest EV penetration – at 46% of their car fleet.

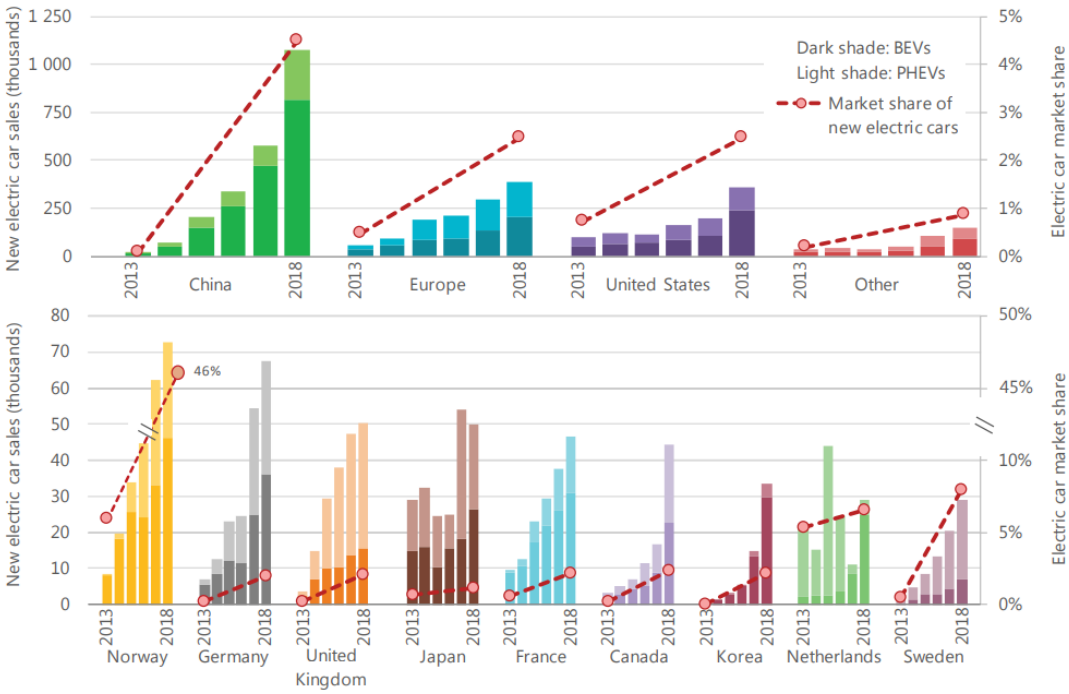

Figure 1.2: Global electric car sales and market share, 2013-18. Source: International Energy Agency

1.2.2 Electric Vehicle Charging

Two parameters key to the overall energy and peak power demand of EV charging are their battery capacity and the power at which they can be charged. EVs on the market today are generally powered by lithium-ion batteries with energy storage contents ranging from 10-100 kWh [31, 33–37]. Typical energy consumption values are in the range 0.1-0.25 kWh/km [38], giving them a driving range of 100-600 km. Most models support both AC charging via an on-board AC/DC converter (in which the maximum charging power is limited to the rating of the converter) and DC charging, which bypasses the on-board converter. Generally speaking, AC charging is used for home, work and some public destination charging points where the duration of stay is longer and therefore the required charging power is lower, typically 3-22 kW [39]. DC charging is used for en route charging points (such as at motorway service stations and petrol station forecourts) where the EV driver is forced to wait while the vehicle charges; therefore, the required charging power is higher. These chargers are generally confined to such locations due to their significantly higher cost compared to AC chargers (because of the AC/DC converters required). At present, DC en route charging power is in the range 50-150 kW [40], though this is expected to increase in the near future. These likely future developments are discussed extensively throughout this thesis.

The time taken to charge an electric vehicle is a subject of much discussion, both in terms of the impact of the convenience of using an EV and the level of flexibility of EV charging afforded to the power system. As an example of the latter, if a 40 kWh EV arrives home with a state of charge (SoC) of 50% (corresponding to an energy storage content of 20 kWh) and it has access to 7.4 kW charging, then accounting for some conversion losses the time taken for the vehicle to be charged to 80% will be under 2 hours; the time taken to be charged to 100% will be in the region 4 hours[3]. However, if the vehicle is parked for 14 hours between arriving at home at 18:00 and leaving again at 08:00 the next morning, this charging demand can be spread in time substantially.

[3]This non-linear relationship in the time taken to charge an EV is the result of how lithium-ion batteries are charged. This is discussed further at multiple points in this thesis, e.g. Section 2.2.5

1.3 The Four Charging Archetypes

1.3.1 Overview

The investigation presented in this thesis is based on the hypothesis that there are a set of four charging archetypes set by location and flexibility, and that any charging event undertaken can be broadly categorised into one of these archetypes. These archetypes are shown in Figure 1.3 in terms of typical locations, power ratings and charging window (i.e. the time during which the required energy can be carried out).

\- *POWER* +

	Domestic	Workplace	Public	En Route
Location	At home – off-street and on-street	Workplace car parks	Supermarkets, shopping centers, on-street (public), public car parks	Motorway service stations, charging forecourts
Power rating	< 10 kW	< 10 kW	10 – 50 kW	> 50 kW
Charging window	> 9 hours	3-9 hours	20 minutes – 3 hours	< 20 minutes

\+ *FLEXIBILITY* -

Figure 1.3: Charging archetypes as defined by typical locations, charging window and charging power

The combination of the rated power and the charging window sets the flexibility of the charging event. While the former can be set by the provider of charging infrastructure – given any physical network limits – the latter is dictated by individuals' travel habits: specifically, the variation in vehicles' arrival time and their duration of stay. While it is not proposed that charging sessions of a given type are uniform (e.g. individuals do not *always* spend at least 9 hours at home), justification of the charging windows in Figure 1.3 is made on the basis of analysis of large-scale travel data in Section 1.3.2.

1.3.2 Justification for the Four Charging Archetypes

The UK National Travel Survey (NTS) is an annual household survey in the UK designed to monitor trends in personal travel. It is used at several points during this thesis, as it presents a large and useful data source on how, when and where people travel. Around 15,000 people are surveyed each year, and the results are available from the UK Data Service [41]. In this thesis, the dataset is used to synthesise vehicle-based travel diaries containing week-long diaries of car-based trips[4]. In this section, analysis of these car-based diaries from the 2016 NTS are used to support the hypothesis regarding charging archetypes.

Parking Locations

Figure 1.4 shows the average proportion of time spent by cars at different locations throughout the 2016 NTS. Note that 'work' is defined as 'work' or 'education' as quoted from the NTS; public is defined as the following locations as quoted from the NTS: 'food shopping', 'non-food shopping', 'eat/drink with friends', 'day trip', 'sport: participate', 'personal business eat/drink', 'other social', 'entertain/public activity', 'personal business other', 'personal business medical'.

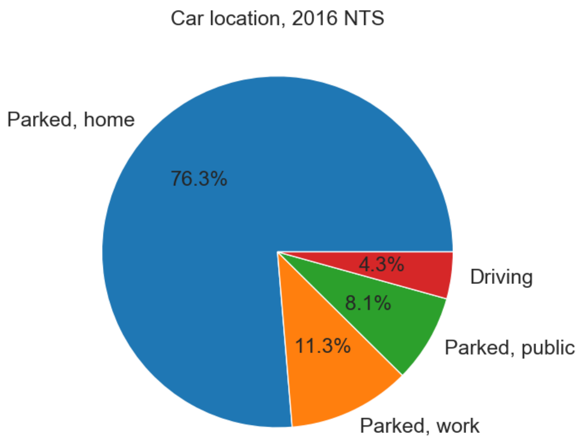

Figure 1.4: Pie chart showing location of car parking by proportion of time, 2016 UK National Travel Survey car-based trips ending at home (left), work (centre) and public destinations (right)

[4]The method by which this is done is detailed in Section 2.2.1

Based on the 2016 NTS, the average car spends 95.7% of its time parked (this is in agreement with the earlier quoted value of 96% from [21]). The vast majority of this parking time is spent at home, followed by work and then public places. The order of time spent at each location provides justification for the order of flexibility of charging archetypes in Figure 1.3.

Figure 1.5 shows the probability of a random car in the 2016 NTS data being parked at home, work or public location for a weekday (Tuesday, left) and a weekend day (Saturday, right).

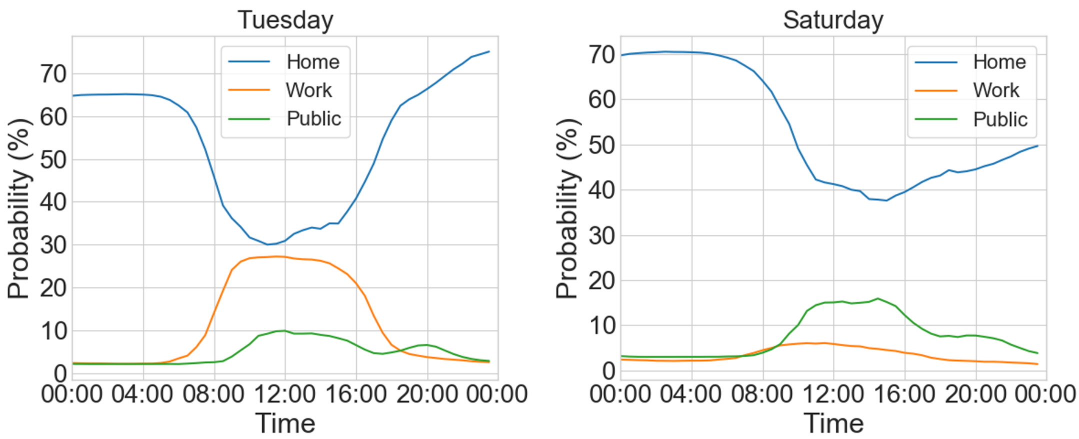

Figure 1.5: Probability of car being parked at home, work and public locations, Tuesday (left) and Saturday (right)

As the charts in Figure 1.5 were taken as a snapshot from a week-long travel diary, the probability of cars being parked on a particular night does not necessarily align with the next. This is particularly evident for the Saturday chart (right), where substantially fewer cars are parked at home late at night compared with the previous night. This is likely to be due to weekend trips away; drivers leaving their homes on Saturday and returning on Sunday. Also, the sum of the three lines at any point does not necessarily add up to 100%. This is due to a proportion of the vehicles being in motion, and another proportion being parked at a set of locations that are not counted as public destinations (this is further discussed in Section 2.2.2).

Figure 1.5 shows that cars are more likely to be parked at home than anywhere else for all times of the day, both during weekdays and weekends. As could be expected, cars are more likely to be at home overnight and more likely to be at work and public places during the day: this drives the time of day during which charging at home, work and public places will most likely be sought.

Arrival Time and Parking Duration

Figures 1.6 shows the distribution of parking event arrival time for home, work and public parking locations.

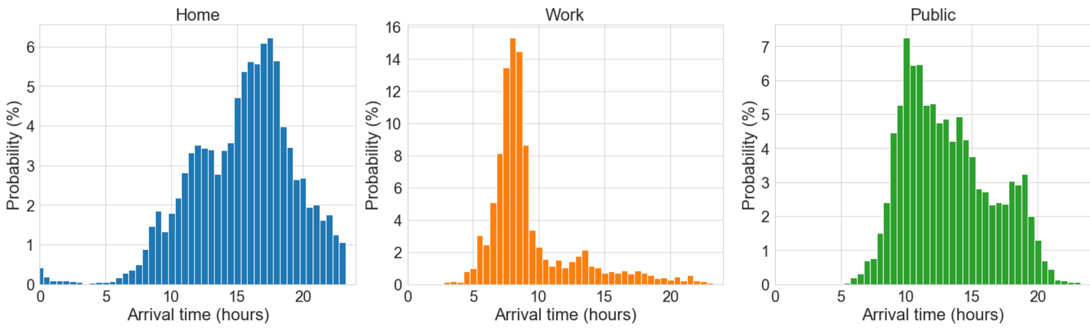

Figure 1.6: Histograms showing parking event arrival time, 2016 UK National Travel Survey car-based trips ending at home (left), work (centre) and public destinations (right)

Of the 58,786 car-based trips ending at home, 29,940 (51%) arrived between 15:00-20:00. Of the 14,463 car-based trips ending at work, 9,346 (65%) arrived between 07:00-10:00. Of the 29,940 car-based trips ending at public destinations, 21,115 (71%) arrived within the period 09:00-16:00.

Of the three locations, arrivals at work were the most concentrated (with the most distinguished peak) whereas home and public arrivals were more spread out (though interestingly, they resemble reflections of one another: whereas arrivals at public locations were most likely in the mid-morning, arrivals at home were most likely in the mid-afternoon).

These arrival times will fundamentally drive the demand for EV charging. Of particular concern is the fact that arrivals at home coincide with the existing electricity network peak. Of course, this is not coincidental: the network peak occurs in the evening because household active occupancy and electrical appliance use is at its highest, which ties in with people arriving home from their daily activities.

Figure 1.7 shows the distribution of parking event duration for home, work and public parking locations.

Figure 1.7: Histograms showing parking event duration, 2016 UK National Travel Survey car-based trips ending at home (left), work (centre) and public destinations (right)

Parking duration drives the flexibility of charging event, and therefore i) the charging power at which the energy must be delivered and ii) the extent to which the charging demand can be shifted in time.

The most likely duration of parking event at home was less than 30 minutes, which is not consistent with the 9 hours value in Figure 1.3. However, it is suggested that this is due to the sheer number of trips ending at home (of 103,189 trips shown in Figure 1.7, 58,786 (57%) ended at home) and that there is little shortage of lengthy parking events at home: during the week of the survey, 81% of the 15,153 individuals never left home without returning for a parking event of at least 9 hours within 24 hours of leaving. 40,959 (69%) of those trips ended in parking events longer than 9 hours.

Similarly to the arrival times, the duration of work parking events were concentrated around a fairly small variance; this is clearly indicative of commuting patterns based on a typical working day of 8-9 hours. Parking events at work were rarely short: 13,213 (91%) were parked for at least 3 hours. Parking events at public places were the shortest of the three locations: 25,535 (85%) were less than 3 hours in duration.

The relationship between parking event arrival time and duration is also important to consider. Figure 1.8 shows density scatter plots of the duration of parking event (i.e. the difference in time between the arrival time and the departure time of the next trip) against the arrival time for trips ending at home, work and public destinations respectively.

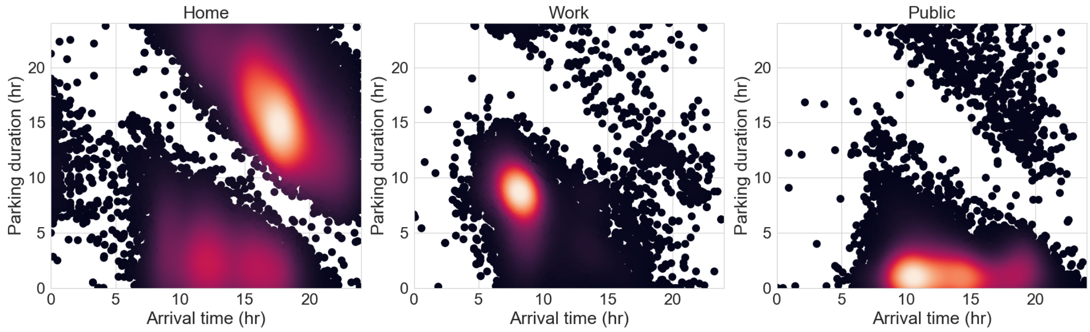

Figure 1.8: Density scatter plot showing parking event duration vs. arrival time, 2016 UK National Travel Survey car-based trips ending at home (left), work (centre) and public destinations (right)

Figure 1.8 allows the visualisation of the likelihood of parking duration, given the time of day. Most significantly, whereas Figure 1.7 shows that home parking durations are most likely to be short (less than 30 minutes), Figure 1.8 shows that the highest concentration of parking events are ones with arrival times in the period 15:00-20:00 and durations of 9-18 hours. It is an important result that the parking events that occur during the period of the existing network peak are most likely to involve long parking stays – and hence the charging events that take place during these parking events tend to be flexible.

In addition to parked charging, EVs have to charge en route when opportunities for parked charging are insufficient to meet the energy demand of their travel requirements. This action is analogous to a petrol station stop for an ICV, and the driver must wait until the EV is charged to the desired amount.

1.4 The Power System and the Smart Grid Paradigm

1.4.1 Traditional Network Design

Traditionally, the GB power system was unidirectional. Power was generated at large thermal plants, using the heat from burning fossil fuels or nuclear fission to drive turbines coupled to electrical generators. These power stations were either built close to the fuel source (e.g. coal mines) or a source of cooling (e.g. the sea), so a large transmission system was designed and built to transport the bulk power for long distances to the centres of demand (i.e. our towns and cities). To minimise losses, this transmission system operates at a high voltage – 275-400 kV in England & Wales and 132-400 kV in Scotland [42]. The distribution system transports this power from grid supply points (GSPs) to the point of use, stepping the voltage down progressively to the point at which it is used by the consumer. For some industrial customers, power can be used at higher voltages, often at 11 or 33 kV. For residential customers, power is stepped down to 230/400 V (single/3 phase). The majority of domestic premises in GB are connected to single phase supplies [43].

Historically, distribution networks were designed on a basis known as 'fit and forget': networks were designed to a certain capacity, based on the peak demand that engineers would expect the network to experience, given some level of acceptable risk [44].

1.4.2 The Smart Grid Paradigm

The decarbonisation of the electricity system has thus far been based on replacing carbon-intensive generators (such as gas and coal plants) with RES generators such as wind turbines and solar photovoltaics (PV). This has been coupled with a decentralisation of electricity generation; whereas traditionally generation was done in bulk, much of the recently installed RES capacity is located within the distribution networks, which were originally designed only for consumption. While traditional generation is dispatchable, intermittent generation is not and forecasting its output (generally based on variations in the weather) becomes difficult at 12 hours or more ahead of real time [45]. This increases the need for power system i) flexibility, to better match consumption with generators' output, and ii) 'schedulability', the ability to plan levels of consumption or generation over a period of time such that inflexible demand can be met at least cost, and energy reserves for ancillary services such as frequency containment can be made available at the right times.

While there are a multitude of methods available to decarbonise the heat and transport sectors, a prominent one is the electrification of those sectors coupled with the continued decarbonisation of the electricity that supplies these demands. Shifting all this energy demand to the electricity sector will significantly increase the demand it sees and, under a ‘fit and forget’ regime, would require an enormous programme of works to upgrade most of the electricity system installed today.

The ‘smart grid’ is essentially a set of technologies that can be used to avoid or defer that investment; to enable a greater penetration of so-called ‘low carbon technologies’ of both generation (e.g. distributed RES) and demand (e.g. EVs, heat pumps) for a given amount of network, and to maximise the utilisation of system assets. It is essentially a power network with communications; one that allows the bidirectional flow of power and information. In this way, the smart grid paradigm can be viewed as making distribution networks more like transmission networks – which already allow bidirectional power flow and are rich in sensors and control equipment. Devices associated with the smart grid include battery storage, EVs, heat pumps, distributed generation and power electronics. The management of consumers’ relationship with electricity and how they demand it, from the implementation of dynamic tariffs in which prices vary according to the time of day or local network conditions to the evolution of an ‘energy as a service’ market [46], is also included as a key part of the smart grid paradigm.

EV charging and the smart grid are symbiotic. The smart grid has the potential to allow EV charging to be managed in a way that provides drivers with the energy necessitated by their travel habits at a considerable reduction in the peak demand that the network would see otherwise. Moreover, the potential of EVs to benefit the power system could not be done without the smart grid. Increasing penetration of RES, which tends to be interfaced to the grid via AC/DC converters, results in fewer synchronous AC sources and a loss of power system inertia[5] [48,49]. By providing grid services such as

[5]Power system inertia can be thought of as the system’s tendency to resist change in its motion, given external forces. Our (traditionally) relatively high inertia system is a product of having large amounts of spinning metal (thermal power plants) coupled to generators. By replacing these with DC-interfaced generators which are not directly coupled (and therefore do not contribute to power system inertia), the system’s inertia (tendency to resist change) is reduced. Lower inertia results in a higher rate of change of frequency following a disturbance [47], and as such high RES power systems can be more vulnerable to sudden deviations in grid frequency, potentially leading to cascading failures of power system assets and loss of load.

frequency response, EVs have the potential to help the power system maintain stability in a high RES scenario [50]. Furthermore, the inherent flexibility of EV charging means that EVs have the potential to provide demand when intermittent renewable energy is in surplus. This has the potential to both reduce the carbon emissions associated with EV charging and reduce the wasted energy from renewable generators.

1.5 Contribution of This Work

1.5.1 Research Questions

The work presented in this thesis seeks to answer the following research questions:

1. What is the likely level of inconvenience (in this case, quantified by the total time penalty) associated with charging an EV, given different levels of technical parameters (battery size, charger power) and level of access to charging?

2. With particular regard to those individuals who cannot charge at home: what are the likely resulting demand profiles from EV charging at i) en route 'forecourts' (in which EVs stop to charge during journeys) and ii) public destinations (in which EVs charge while parked, as their users are engaged in some activity that brought them there)?

3. What is the likely impact of domestic EV charging on residentially-dominated distribution networks, and how is this likely to vary with i) drivers' charging behaviour, ii) the socioeconomic make-up of the network and iii) the evolution of the EV market, in terms of changing battery size, charger power and level of access to charging?

4. What is the potential for 'smart' EV charging to i) manage the vehicles' energy demand within network constraints and ii) interact positively with the power system by reducing the carbon emissions associated with EV charging and absorbing excess renewable energy generation that would otherwise be curtailed?

1.5.2 Overview of Chapters

The work is divided into six chapters including this one; a brief description of the contents of each chapter is given below.

- Chapter 2 seeks to investigate the ease of a transition to electrified private transport from the point of view of the consumer. An investigation of the inconvenience of EV charging relative to ICV fuelling is presented, in terms of the time penalty likely to be experienced by drivers for different combinations of battery capacity, charger power and access to charging at different locations (home, workplace and public destinations). It was found that there is likely to be a significant difference in the time penalty associated with EV charging depending on the level of access to charging that the driver has – though increasing battery capacity and charger power is predicted to reduce this difference. Following from this conclusion, two things are made clear: i) widespread public and en route charging will be an integral part of the EV charging mix; ii) domestic charging is likely to be the most 'useful' form of charging in minimising the inconvenience of EV use and therefore if drivers have access to it, it is expected that most of their charging events will be carried out at home.

- Chapter 3 presents a set of methods developed to characterise charging demand at public charging facilities using smartphone locational data, based on findings from Chapter 2 that under high penetration of EVs, a significant amount of their charging will be based on public charging, both en-route and at public destinations such as supermarkets, shopping centres and cinemas where drivers leave their cars for time periods ranging from 15 minutes to 3 hours. It was found that the temporal variation in demand at these locations is likely to vary significantly based on the day of the week and the location at which charging is installed: for example, whereas gym-based EV charging demand is likely to peak on Monday evenings, the corresponding peak in supermarket-based EV charging demand is likely to occur on Saturday afternoons. The techniques presented in Chapter 3 could be invaluable to both transport and power system planners as the EV market – and hence the demand for public/en route charging – grows.

- Chapter 4 presents a set of methodologies for assessing the impact of residential EV charging on distribution networks if all charging is uncontrolled. The effects of charging behaviour, the demographics of the EV drivers and the parameters of the EVs on the resulting charging demand and impact to the network are investigated. It was found that there is potentially a large gap in the temporal variation in EV charging demand and the resulting impact on distribution networks depending on how drivers plan their charge events, based on two models of charging behaviour: i) one in which drivers will seek to minimise the number of plug-ins, and ii) one in which drivers will routinely plug in upon arrival at home. It was found – through case studies of two real distribution networks in the Southside region of Glasgow – that the social demographics of the individuals served by a given network are likely to impact the resulting impact from EV charging, mainly as their travel requirements are likely to be different. Finally, it was found that changing EV parameters (battery size, charger power) and the level of access to charging afforded to the drivers has a significant effect on the resulting EV charging demand and the impact to the network: there are certain patterns in the evolution of the EV market that would appear to reduce the burden on networks, and there are some that would appear to increase it.

- Chapter 5 presents an investigation of the potential for controlled (a.k.a. 'smart') charging to reduce the impact of EV charging on the network and enable EV charging to further benefit the power system by providing demand to utilise surplus of renewable generation. A comparison is presented between a formal optimisation of charging and simpler, low-information heuristic-based methods that would be easier to adopt in practical networks. It was found that for an EV penetration of 100%, their charging is likely to lead to undervoltages on the same network as analysed in Chapter 4, even if all charging is scheduled via a 'valley filling' optimisation approach in which the minimum network loading is sought over a 24-hour period. It was found that 'smart' EV charging does have the potential to interact positively with the power system. Through selectively charging when grid carbon intensity (gCO_2/kWh) is low, the emissions associated with their driving (gCO_2/km) can be reduced to a level a fifth of that of an average new petrol or diesel car sold in Europe, based on charging from the current GB grid. A fleet of 500,000 EVs in Scotland (corresponding to a penetration of approximately 20%) could absorb over three quarters of curtailment at Scotland's largest onshore wind farm.

- Chapter 6 draws conclusions and suggests further work from this thesis.

1.6 Publications and Other Contributions

The following journal publications have been published or accepted for publication at the time of writing:

1. J. Dixon, P. B. Andersen, K. Bell, and C. Træholt, "On the ease of being green: an investigation of the inconvenience of electric vehicle charging," Applied Energy, vol. 258, 2020. doi: 10.1016/j.apenergy.2019.114090

2. J. Dixon, I. Elders, and K. Bell, "'Evaluating the likely temporal variation in electric vehicle charging demand at popular amenities using smartphone locational data," IET Intelligent Transport Systems, 2020. doi: 10.1049/iet-its.2019.0351

3. J. Dixon and K. Bell, "Electric vehicles: battery capacity, charger power, access to charging and the impacts on distribution networks," eTransportation, 2020. *Accepted/in press*

The following journal submission has been made, which is currently under review:

1. J. Dixon, W. Bukhsh, C. Edmunds, K. Bell, "Scheduling electric vehicle charging to minimise carbon emissions and wind curtailment," 2019. *Submitted to Renewable Energy Special Issue on "Renewable Energy to Drive Sustainable Electric Transport: Synergies, Challenges and Opportunities" on 17th November 2019*

The following published conference papers:

1. J. Dixon, I. Elders, and K. Bell, "Electric vehicle charging simulations on a real distribution network using real trial data," in Proceedings – 2019 IEEE Transportation Electrification Conference & Expo Asia-Pacific, Seogwipo-si, Korea (South), 2019.

2. J. Dixon, I. Elders, and K. Bell, "Characterization of electric vehicle fast charging forecourt demand," in Proceedings – 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe ISGT-Europe 2018, Sarajevo, Bosnia Herzegovina, 2018.

3. J. Dixon, I. Elders, and K. Bell, "Opportunities for interconnection of adjacent distribution feeders in GB networks," in Proceedings – 2017 Universities Power Engineering Conference (UPEC), Heraklion, Greece, 2017.

The following contributions to conferences:

1. "On the Ease of Being Green", ETP Annual Conference, Dundee, UK. 2019.

2. "A Discussion on the Electrification of Private Transport" (Invited Speaker and Panellist), Scottish Transport Show, Edinburgh, UK. 2019.

3. "Electric Vehicle Charging: How 'Bad' Might it be?", CIGRE UK Evening Event – The Challenges of Connecting Electric Vehicles to the Grid, Birmingham, UK. 2019.

4. "Local Network Impacts of the Electrification of Transport", UKERC Annual Conference, Oxford, UK. 2019.

5. "Electric Vehicle Destination Charging Demand Characterisation", E-Mobility Power System Integration Symposium, Stockholm, Sweden. 2018.

6. "CIGRE Next Generation Network Showcase: Using Smartphone GPS Data to Characterise Destination EV Charging Demand", CIGRE 2018 Showcase, Paris, France. 2018.

7. "Modelling EV Charging Behaviour and its Impact on the Grid", UKERC Annual Assembly, Sheffield, UK. 2018.

The following published blog posts:

1. J. Dixon, "What will the electric vehicle revolution mean for our electricity system?," Centre for Energy Policy, 2018. [Online]. Available: https://bit.ly/350fsSU.

2. J. Dixon, "Electricity System Change: Flexibility and Costs," UK Energy Research Centre (UKERC), 2018. [Online]. Available: https://bit.ly/2YprwLn.

The following technical reports:

1. J. Dixon, K. Bell, "NIA 'Reflect' Data Assessment," Electricity North West Limited Reflect Project [Online]. Available: https://bit.ly/2DUNLiw

2. M. Hannon, E. Topham, J. Dixon, D. McMillan, and M. Collu, "Offshore wind, ready to float? Global and UK trends in the floating offshore wind market." 2019. doi: 10.17868/69501

And the following achievements:

1. 2$^{\text{nd}}$ prize, poster competition, 2019 ETP Annual Conference, Dundee, UK.

2. Best Paper Award, 2019 IEEE Transportation Electrification Conference & Expo Asia-Pacific.

3. Winner, CIGRE Next Generation Network Presentation Competition 2018, University of Manchester, UK

4. Peoples' Choice award, 3 Minute Thesis competition 2018 (University of Strathclyde final).

As per the terms of this work's funder, the Engineering & Physical Sciences Research Council (EPSRC), all published journal & conference papers (accepted author manuscripts) and presentations given at conferences are available open access on the author's PURE webpage [51]. All data have been archived and, in accordance with EPSRC rules, all data originating from this work can be accessed on request.

Chapter 2

On the Ease of Being Green: The Inconvenience of Electric Vehicle Charging

2.1 Introduction

2.1.1 Barriers to Electric Vehicle Adoption: Realities and Perception

A major obstacle to widespread EV adoption is the perception that their charging carries a significant amount of inconvenience relative to the fuelling of ICVs. This perception is grounded in two facts:

1. Battery storage is far less energy dense than the storage of hydrocarbon fuels in a tank. The US Department of Energy assumes the energy content of a US gallon (3.89 litres) of petrol to be 33.7 kWh [52]. On this basis, even a small 'city' ICV model such as a 2018 Fiat 500 with a 40 litre petrol tank [38] effectively has an energy storage capacity of over 340 kWh, compared to 40 kWh available in the 2018 Nissan Leaf, an EV at the lower end of the market in terms of price [53]. Due to the significantly greater losses associated with the combustion engine of an ICV than those associated with the motor and traction drive of an EV [54], EVs can travel around 3-4 times further on the same amount of energy storage.

However, differences in vehicles' energy storage capacities still imply a large gap – at least for now – between the ranges of EVs and similarly priced ICVs.

2. EV battery charging must be done at a far slower rate than fuelling an ICV. Whereas even the highest projected power ratings of future EV charging mentioned in academic and industrial literature are limited to hundreds of kW [55–59], the effective 'charge rate' of a light passenger ICV is around 5000 kW taking into account combustion engine losses [60]. This implies that – at least for now – charging EVs will take more time than fuelling ICVs.

In contrast, whereas the fuelling of an ICV must be done by the user as they stand at a petrol pump, having visited a petrol station specifically to replenish the energy storage content of their vehicle – an activity that was found to take around 3-5 minutes (Section 2.2.9) – an EV can be charged while it is parked at home, work or in another private or public location with a significantly smaller time penalty associated with plugging in and removing the charging cable. The only occasions when users will have to wait for their EV to be charged are when, on a long journey or on multiple trips lacking an opportunity to charge at destinations, the battery's SoC has reached such a level that the user must make a specific charging stop. If the total duration of these occasions was less than the total duration of fuelling stops at petrol stations required by ICVs, it could reasonably be argued that charging an EV is of greater convenience than fuelling an ICV. The frequency and duration of charging occasions would depend on the battery capacity of the EV, the rate at which it could charge its battery and its access to a variety of charging locations (e.g. at home, work and public destinations).

Several studies have examined the physical limitations of electric transport. Axsen et al [61] establish that battery technology limitations and high battery cost are the major obstacles to widespread adoption of EVs. The study reflects on the fast pace of development of EV battery sizes and charging capacities in the goal of attaining a level at which they will, suddenly, become acceptable to most users. The question on how much range an EV needs is multi-faceted in both technological and social contexts. Pearre et al [60] conduct a study on a year's worth of real vehicle monitoring data to establish the required range to complete a day's driving (it is assumed that vehicles can charge every night and start the next day with a full battery). It was found that 21% of drivers in the sample could substitute their ICV for a modern EV in the 'affordable' sector of the market such as the 40 kWh capacity, 150-mile range 2018 Nissan Leaf [38] without a single day of adjustment to their normal travel schedules, while 60% of drivers from the same sample could substitute for the same EV if they were willing to make adjustments to six days in the year.

Although the results presented in the literature suggest that in most cases there is only a slight adjustment of lifestyle required for the adoption of an EV, consumers remain resistant to EVs [62]. While this may partially be due to a tendency to resist the adoption of any new technology due to lack of knowledge, high initial costs and low risk tolerance [63], the main reason for a consumer not wanting to substitute their ICV for an EV is usually cited as so-called 'range anxiety' [64–67], so much so that the willingness to pay to extend driving range is reported as being between €30-100 per additional km [65,66]. In [67], Franke et al compile responses from surveys of the acceptable range an EV would have to have before a consumer would consider the substitution of their ICV for one; all six of the comparable studies cite a range of at least 300 km.

The subject of long journeys and the perceived inconvenience of having to stop to charge multiple times is clearly an important one to would-be EV consumers. However, it is suggested that natural breaks taken as part of long journeys regardless of the vehicle's propulsion system are overlooked; if the driver could fit necessary charging sessions into natural breaks then the inconvenience of using an EV for that journey would be reduced.

2.1.2 Contribution

The key contribution of this chapter is the quantification the inconvenience – defined as the total time penalty – of EV charging based on the analysis of 39,020 week-long travel diaries synthesised from the NTS dataset, originally introduced in Section 1.3. The charging time penalty is assessed in respect of two types of charging event: one where the vehicle is parked at home, work or a public destination; the other en route.

In both cases, a time penalty is applied associated with the time taken to plug in and remove the charging cable. However, in the former type of charging event it is assumed that while the car is parked, the user is engaged in an activity that is unaffected by how they came to be at that location and therefore is not inconvenienced by the use of an EV. In the latter, it is assumed that the user is inconvenienced by being forced to wait for the car to be charged and so the charging time is added as a further time penalty. The charging time penalties are evaluated by a heuristic algorithm presented in this chapter that derives an idealised charging schedule for each travel diary such that the vehicle's SoC is kept above a prescribed level throughout subject to the minimum number of charging events, scheduling parked charging events before resorting to en route charge events because of their smaller time penalty.

This analysis is carried out for different EV battery capacities, charger power ratings and levels of access to charging locations (i.e. home, work and public destination) and the results are compared to the expected time penalty associated with ICV fuelling for the same travel diaries, based on a fixed time penalty associated with each fuelling stop. This allows the quantification of combinations of battery capacity, charger power rating and level of access to charging at different locations necessary for would-be EV drivers to be able to switch their ICV for an EV without suffering an amount of inconvenience, given the same travel habits.

Particular attention is paid to long journeys – those whose distance is greater than can be made on a single charge – to investigate the likely inconvenience added to these journeys as a result of charging, given that at least some charging can be fitted into natural breaks that are taken on long journeys. Analysis is carried out for two cases: one where it is assumed that drivers follow UK Highway Code Rule 91 [68] which mandates 15 minutes' rest for every 2 hours of driving, and a sensitivity case where it is assumed drivers take a 15 minute break only once every 4 hours.

2.1.3 Simplifying Assumptions

Idealised Charging Schedules

The modelling presented in this chapter minimises the level of inconvenience that both EV and ICV users would experience by representing idealised charging and fuelling behaviour. While this assumption will affect the time penalty suffered by EV users more than that suffered by ICV users due to their shorter range and therefore greater number of charging/fuelling stops, EV users' ability to learn the charging requirements associated with their vehicles and minimise the number of times it needs to be plugged in has been observed [69, 70]. Although a driver's actual charging pattern may differ from that derived in the model, drivers are likely to exploit opportunities to charge when the vehicle would be parked anyway and their desire to minimise dependency on en route charging are likely to give comparable results in respect of inconvenience. To assist the driver in minimising their charging inconvenience, smartphone apps such as Zap-Map's Journey Planner [71] are available that, given access to a driver's planned journeys and public data on charger locations, will advise the driver on the optimal charging schedule.

The potential value of a sensitivity study to the effect of human behaviour and 'non-ideal' decision making in the scheduling of EV charging and the resulting inconvenience is suggested as a piece of further work in Section 2.5.

Availability of Charging and Fuelling Infrastructure

In the absence of any data allowing a comparison to be made on the time taken to find an EV charger or petrol station, this study does not consider any inconvenience associated with finding an EV charger or petrol station, and it is assumed that i) an EV charger is available at any home, work or public destination providing the EV in question has that level of charging access, and ii) an EV charger or petrol station is immediately available at the point an EV or ICV reaches a minimum range of 25 km remaining, taken to represent the smallest amount of charge that a prudent driver would be willing to have in the battery or fuel tank.

While this is anticipated to have a significant impact on the results presented, the assumption can be justified by considering the following. If a driver has access to charging at their home or workplace, then they are expected to be able to use that charger whenever they need to, as these destinations are likely to be the same physical locations every time. The main exceptions to this would be if another vehicle at their home is using the household charger or if provision of charging at their workplace is insufficient to service the number of EVs that require charging. Public charging is different, as these destinations are likely to correspond to a much larger set of physical locations. Here, the successful access rate of charging would depend on whether the public destination in question has EV charging infrastructure installed. The assumption is made that EV charging infrastructure can be found at any of a set of public locations detailed in Section 2.2.2; in doing so, the results of this chapter reflect a scenario where EV charging infrastructure is plentiful. According to [39], there are currently (as of September 2019) 25,959 public EV charging connections across 9,580 locations in the UK and the number of connections has increased by over 45% in the last 12 months. Compared to the total number of UK petrol stations of 8,422, which is in a continuing trend of decline [72], EV charging infrastructure is clearly gaining itself a greater presence. Furthermore, [73] and [74] both suggest that EV drivers are likely to actively seek out destinations (such as supermarkets, hotels and restaurants) that offer charging opportunities, and journey planning smartphone applications such as [71] will assist drivers in finding them. This suggests a commercial incentive on such destination charging being made available in order to attract custom from EV owners reliant on public charging, as is already being seen: for example, as of August 2019, three of the UK's biggest supermarket chains have announced plans to install free-to-use EV charging infrastructure at their stores by 2020 [75–77].

As this assumption is likely to significantly affect the results presented, the consideration of non-binary levels of access to charging at locations is highlighted as a valuable piece of further work in Section 2.5.

Boundary Conditions

To offer a fair as possible comparison between the time penalties associated with charging an EV and fuelling an ICV over the course of a week-long travel diary, the charging schedules were derived on the basis such that the energy content of the vehicle at the end of the travel diary must be equal to that at the start. It is assumed that an EV's initial SoC (and therefore the SoC it must end its travel diary with) is 80%, given that the time taken to charge between 80-100% is disproportionately longer than the time taken to charge between 0-80% (this is further explained in Section 2.2.5). By comparison, an ICV's fuelling time penalty is calculated as a proportion of a fixed (minimum fuel level to full tank) fuelling time penalty, according to the volume of fuel it consumes over the course of the travel diary. Effectively, it is assumed that an ICV will wait until it reaches the minimum fuel level before carrying out a full refuel – the most time-efficient fuelling action possible.

Charging During Long Journeys

In this chapter it is assumed that drivers would try to fit EV charging on a long journey into natural breaks – taken regardless of the vehicle's form of propulsion – wherever possible, given that such breaks are often taken where charging infrastructure is increasingly present, e.g. motorway service stations [40]. Therefore, the en route charging time penalty is adjusted to account for any breaks taken. To allow fair comparison, the same analysis is carried out for ICV fuelling on long journeys.

Although there is data in the NTS for breaks taken during journeys (given by the difference between the fields 'total time' and 'trip time'), it is suggested that these are likely to be under-reported: 82% of journeys over 200 km and 77% of journeys over 4 hours are without any recorded breaks. Due to the likely unreliable nature of this data, this chapter assumes a constant rate of breaks per driving time for one of two cases: in the first case it is assumed that all drivers are compliant to UK Highway Code Rule 91 [68], in which 15 minutes' break is advised for every 2 hours of driving. As it is recognised that this has a considerable effect on the resulting inconvenience of charging and drivers may not be compliant to the Highway Code, a sensitivity case of 'half' Rule

91 – a 15 minute break for every 4 hours of driving – is also presented.

Fixed Arrival Times and Infeasible Travel Diaries

While time penalties are attributed to both parked and en route charging events, arrival times of journeys are not adjusted to account for stops due to charging because there is not sufficient information on how an individual's arrival time would affect a subsequent departure time: on some occasions, such as a visit to a leisure destination, a late arrival would result in a late departure as the time at the destination could be considered fixed. However, on other occasions, such as arriving home from work before leaving the next morning, a late arrival due to a charging stop on the journey home would likely not lead to a late departure time, which could be considered fixed. As a result, travel diaries are not adjusted to account for charging stops. However, the number of travel diaries that are rendered infeasible by the presence of charging (by at least one journey being delayed past the subsequent departure of the next trip) is reported for all variations of battery size, charger power and access to charging at different locations (Section 2.3.3).

Zero Battery Degradation

Lithium-ion batteries degrade with use, a process whose rate depends on a wide variety of factors including temperature, rates of charge and discharge, depth of discharge, SoC and total energy withdrawn [78]. It has been documented in [79] that aged batteries can experience a capacity fade of at least 20%, which would linearly affect the range of the vehicle. While this is acknowledged to affect the resulting inconvenience of charging as vehicles will have to seek more charging opportunities as their battery capacities fade, the first purpose of this chapter is to assess convenience and whether it is rational for inconvenience to influence choice of vehicle when it is being bought new. It is assumed that the entirety of the batteries' capacity can be used, at least initially, save for the minimum range that the vehicle must retain. However, some linear extrapolation can be applied to the results presented: for example, a 20% capacity fade on a 30 kWh battery will result in the EV having an achievable range equal to that of one with a 24 kWh battery, ignoring any differences in the vehicle's energy consumption and any effect on the charging rate attainable following the capacity fade. There are other effects that result from the degradation of batteries, which are discussed as points of further work in Section 2.5.

Constant Unity 'Elasticity' of Inconvenience

The inconvenience resulting from a given time penalty is likely to vary depending on the time of day, and the proximity to events within an individual's schedule deemed to be the most important, e.g. having to stop and charge on the way to work may be seen as a greater inconvenience than doing so on the way home. It is suggested that this pattern is analogous to the variation in Value of Lost Load (VoLL) depending on the activity being undertaken and the relative importance of that activity in an individual's schedule [80]. Furthermore, experiencing multiple time penalties of the same total duration as one larger time penalty would in reality require greater planning and may be perceived as a greater inconvenience. Due to the complex nature of defining the relationship between convenience and time penalty (in a sense, the elasticity of convenience), analysis presented in this chapter assumes that inconvenience experienced is directly proportional to time penalty, regardless of the time at which this penalty is experienced. There is space for valuable further work in this regard, further discussed in Section 2.5.

2.2 Method

2.2.1 Travel Data from the UK National Travel Survey

Insight into individuals' travel habits can be provided by the analysis of travel survey data; that is, self-reported data of trips made by individuals over a period of time. The NTS is one such survey, conducted annually for around 15,000 residents in which they record all trips taken over a 7-day period [41]. The 7-day period recorded differs between the individuals recording the data, hence minimising any bias from seasonal effects and holidays. Data for the years 2012-2016 as used in this study contains details of 598,645 car-based trips made over the period.

To justify use of 5 years' worth of NTS data, Figure 2.1 shows the variation in trip distance (km) and time (minutes) of all car-based trips between years. The mean distance varies only within the range 14.42-14.80 km and the mean time varies within the range 21.38-22.81 minutes (both 2012-2015 respectively). Although the variation within each year is significant as shown in Figure 2.2, the variation between years is evidenced to be very slight.

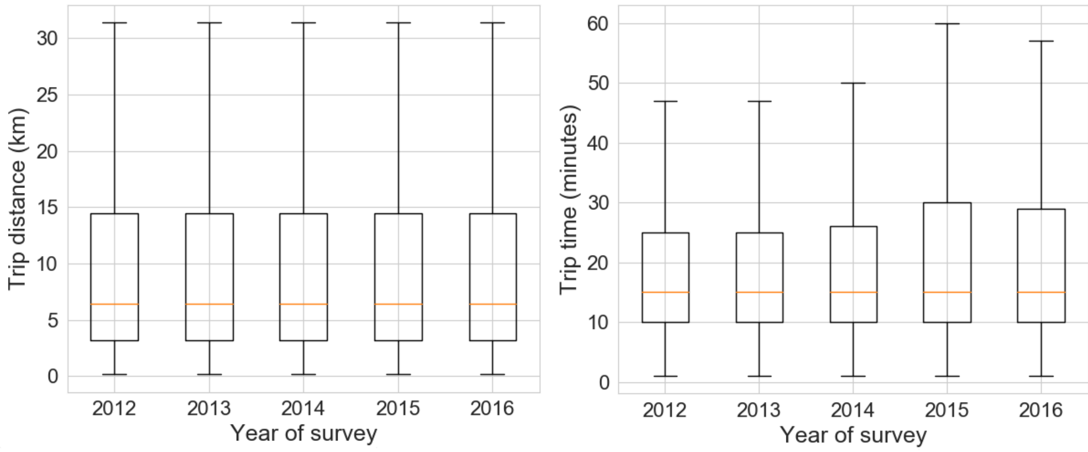

Figure 2.1: Boxplots showing variation in trip distance (km) and duration (minutes) across 5 years of UK National Travel Survey data (outliers omitted for clarity)

The NTS contains two tables of relevance to this study: a trip dataset and a vehicle dataset. The trip dataset contains data pertaining to the distance, duration, time/day of departure, mode of transport and purpose of each trip recorded. Associated with each trip is an ID of the individual who took the trip, but trips are not associated directly with a vehicle. In order to synthesise week-long travel diaries for each vehicle, the vehicle and trip datasets were matched up. The vehicle dataset contains information on each of the vehicles within the NTS, including the ID of the 'lead driver' with whom the vehicle is associated. Note that in the NTS, multiple vehicles can be associated with one individual but a single vehicle cannot be linked with more than one individual. For each individual, a list of vehicles associated with that individual is returned. If the individual is assigned to more than one vehicle (6.6% of the total individuals were assigned to more than one vehicle), then the 'vehicle availability' – which describes how often the vehicle is used – for each vehicle is returned. If only one of the vehicles assigned to this user is described as being in regular use, all trips associated with this individual ID are assigned to the vehicle in regular use. If more than one vehicle is described as being in regular use, then trips are assigned at random to the vehicles that are said to be in regular use by that individual. 5.4% of individuals claimed to have more than one vehicle in regular use. The result of the processing of the NTS dataset is a set of week-long travel diaries for 39,020 vehicles. An example travel diary is shown in Table 2.1.

Table 2.1: Key data fields regarding car-based trips from example NTS travel diary

Trip #	**Distance (km)**	**Origin**	**Destination**	**Trip Start (Weekday, HH:MM)**	**Trip End (Weekday, HH:MM)**
1	3.2	Home	Non food shop	M 10:00	M 10:05
2	3.2	Non food shop	Home	M 10:25	M 10:30
3	16.1	Home	Other social	M 13:30	M 14:00
4	16.1	Other social	Home	M 15:30	M 16:00
5	12.9	Home	Personal business	Tu 11:30	Tu 11:50
6	12.9	Personal business	Home	Tu 11:55	Tu 12:15
7	64.4	Home	Visit friends	Sa 07:00	Sa 07:45
8	12.9	Visit friends	Other social	Su 13:00	Su 13:45
9	59.5	Other social	Home	Su 20:00	Su 20:45

Figure 2.2 shows the spread in data of all 39,020 car-based travel diaries used in this study in terms of the distance driven, the number of trips taken and the total driving time.

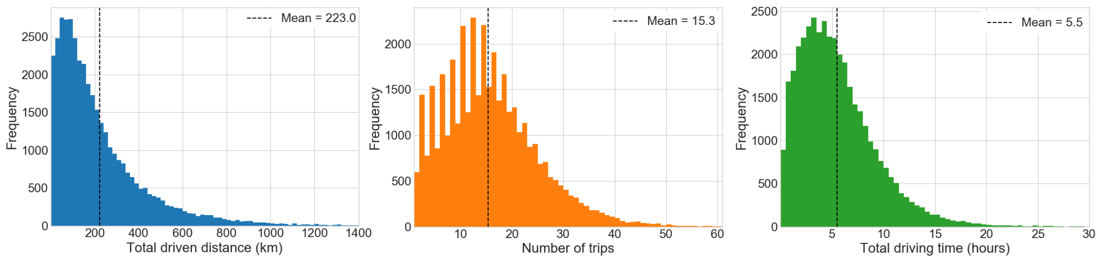

Figure 2.2: Histograms showing spread of distance driven, number of trips taken and total driving time across 39,020 travel diaries synthesised from the UK National Travel Survey dataset

Figure 2.2 shows that there is a significant spread in individuals' driving habits. It is shown that the number of trips is more likely to be even than odd. This is suggested to be due to there being more return trips in week-long travel diaries than one-way trips. The mean corresponds to an average of 1.1 return trips per day. Individuals spent a mean time of 5.5 hours driving in the week covering a mean distance of 223 km. However, the modal times and distances are significantly less than this (approximately 3 hours and 80 km respectively), showing that the small number of individuals who drove considerably more than the majority increase the mean driving behaviour. Due to the large variance in the data, results from the assessment of EV charging inconvenience will be expressed as the total time penalty due to charging (in minutes) per total time spent driving (in hours, as per the data in Figure 2.2), to allow the results to be more easily compared across the spectrum of driving behaviours.

2.2.2 Parameters

Battery Capacity and Energy Consumption

Battery capacities found on variants of two of the highest-selling EVs on the global market are used for reference: the lower-range Nissan Leaf and the longer-range, higher-priced Tesla Model S. The energy consumption values used are taken from the US Environmental Protection Agency (EPA)'s fuel economy test data [38], whose Federal Test Procedure is designed to allow direct comparison of emissions and fuel economy between different vehicles for real-world driving conditions based on city and highway driving cycles. Values used are shown in Figure 2.3 along with battery capacity for the vehicle models discussed.

Charger Ratings

The effect of charger rating is investigated by using 'low power' and 'high power' scenarios (Table 2.2).

The low power scenario is based on 'slow' home charging (single phase 16 A, 230 V) and workplace/public destination charging (three phase 16 A, 230 V); en route charging rate are based on those currently widely available [40]. The high power scenario is based on 'fast' home charging (single phase 32 A, 230 V) and workplace/public destination charging (three phase 32 A, 230 V); en route charging rates are based on projected near-future developments further discussed in Section 2.4.

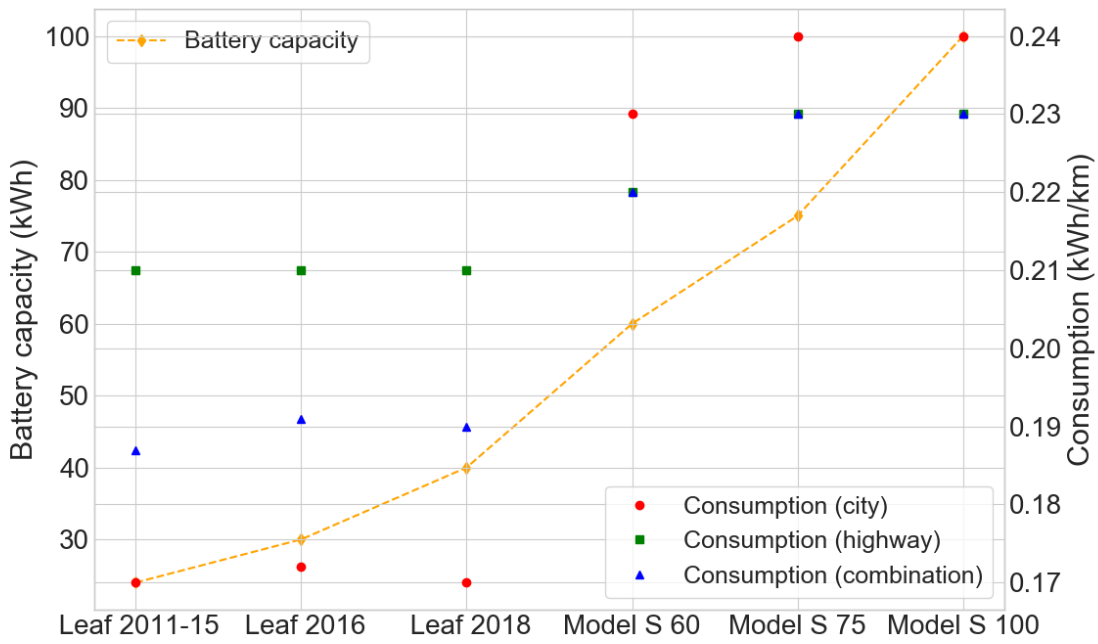

Figure 2.3: Energy consumption values (city, highway and combined) for vehicles considered in study, source: US Environmental Protection Agency

Charging Access

The NTS trip data contains a field on the destination of the journey. For home and work charging, the destination is clear-cut as 'home' for home charging and 'work' or 'education' for work charging. For public destination charging, judgement was taken to ascertain which destinations could likely see charging opportunities. Table 2.3 shows an exhaustive list of destinations from the NTS data (except 'home', 'education' and 'work') and a True or False value to indicate whether vehicles are assumed to be able to charge at that destination. The philosophy of this was to allow charging at locations where chargers are currently found [39] and not at the end of escort journeys (i.e. when the purpose of the journey was to drive another individual to a destination), visiting friends or on holiday.

Table 2.2: Charging scenarios used in synthesis of charging diaries

Charging scenario	**Home Charging (AC)**	**Workplace/ Destination Charging (AC)**	**En Route Charging (DC)**
Low Power	3.7 kW	11 kW	50 kW for battery capacity $<$ 60 kWh; 120 kW for battery capacity $\geq$ 60 kWh
High Power	7.4 kW	22 kW	150 kW for battery capacity $<$ 60 kWh; 350 kW for battery capacity $\geq$ 60 kWh

Table 2.3: Public destination charging availability in study

Public destination charging = TRUE	**Public destination charging = FALSE**
Food shopping	Escort work
Non food shopping	Other escort
Eat/drink with friends	Escort home
Day trip/just walk	Visit friends
Sport: participate	Holiday: base
Personal business eat/drink	Escort shopping/personal business
Other social	In course of work
Entertain/ public activity	Escort education
Personal business other	Escort in course of work
Personal business medical	Other non-escort

2.2.3 Charging Time Penalties

Although one argument made in favour of the convenience of EV use is that they can be charged while the user is otherwise engaged, there is a time penalty associated with plugging in and removing the charging cable. Time penalties for such as used in this study are derived from experiments carried out at DTU PowerLab with a Renault Zoe EV for both fixed cable (in which the cable is already in situ with one end already plugged into the charger, typical of home and en route applications) and loose cable (in which the cable must be taken from the car before plugging in to both the car and the charger itself, typical of work and destination applications). For the fixed cable scenario, the plug-in time is the time taken to walk from the driver's side door to the charger at the front of the car, take the cable from the charger and insert it into the car's charging socket – also on the front of the car. The removal time is the time taken to unplug the cable from the car, return it to the charger and walk to the driver's side door. For the loose cable scenario, the plug-in time is the time taken to walk from the drivers' side door to the car's boot, remove the cable, close the boot, walk with the cable to the charger at the front of the car and use the cable to connect the car with the charger. The removal time is the time taken to unplug both ends of the cable, walk to the car's boot and open it, put away the cable, close the boot and walk back to the driver's side door. Three trials of plugging in and removing the cable for both fixed and loose cable set ups by an individual familiar with the process of EV charging were performed; the results are shown in Table 2.4.

Table 2.4: Experimental results: plugging in and removal time for charging cable

Cable	Plug-in time (s)				Removal time (s)				Total time
Scenario	1	2	3	Mean	1	2	3	Mean	penalty (s)
Fixed Cable	8.3	9.4	8.9	**8.9**	7.3	8.5	8.6	**8.1**	**17.0**
Loose Cable	27.7	27.2	28.2	**27.7**	21.7	21.2	20.8	**21.2**	**48.9**

The total time penalty in Table 3 is applied to every charging event returned. The time taken to charging for each charging type is given as follows:

- For charging while parked at home: a fixed cable time penalty (17.0 s) is applied to each charging event
- For charging while parked at work or a public destination: a loose cable time penalty (48.9 s) is applied to each charging event
- For en route charging: a fixed cable time penalty (17.0 s) is applied to each charging event in addition to the time taken to carry out the necessary charging

Note that although these time penalties are given in seconds, they are converted to hours for all equations presented in this chapter.

The time elapsed between stopping and exiting the car, and between re-entering the car and starting to move again, is neglected in the calculation of both parked and en route charging events. For parked charging events, this is based on the assumption that the driver would be leaving the vehicle regardless of whether a charging action would be taken, because all parked charging events are taken at destinations (home, work or public) that the driver will come to be at regardless of the type of vehicle they arrive in. Therefore, the time penalty of this event is the detour from their intended trajectory, as quantified by the time penalties in Table 2.4. For en route charging events, although the time taken to exit and re-enter the car would represent an additional time penalty, it is negligible in comparison to the time spent charging the vehicle.

2.2.4 Heuristic to Evaluate Idealised Charging Schedule Given a Travel Diary from the UK National Travel Survey

Overview

The total time penalty of EV charging is calculated by a heuristic method that derives an idealised charging schedule to cover the energy requirements of any given seven-day travel diary from the UK NTS. It will return the minimum number of charging events in order to maintain the vehicle's SoC at a sufficient level, choosing parked charging events first and then resorting to en route charging events only when it cannot meet the travel diary's energy requirement by parked charging alone.

The heuristic is based on the assumption that parked charging will always carry a lesser time penalty than en route charging, and will return the optimum charging schedule given this assumption. The following sections describe the process followed by the heuristic presented in this chapter.

Energy Requirement for Travel Diary

$\mathcal{I}$ denotes the set of trips in a vehicle's travel diary. For each trip i, $i \in \mathcal{I}$, the average speed $\bar{v}_i$ (km/h) is calculated from the trip distance d_i (km) and total trip duration D_i (hours) (2.1).

$$\bar{v}_i = \frac{d_i}{D_i} \tag{2.1}$$

The vehicle's energy consumption (Figure 2.3) is defined for three types of trip:

'city', 'highway' and 'combined'. The assignment of a particular journey to one of these types is based on average speed: 'city' for journeys with an average of less than 50 km/h, 'highway' for journeys with speeds greater than 100 km/h and 'combined' for journeys with speeds in between. These speed thresholds are based on free-flow traffic speed recorded on roads in Britain [81].

Following the setting of the vehicle's energy consumption c_i (kWh/km) during trip i, the energy demand W_i (kWh) of trip i is calculated (2.2).

$$W_i = d_i c_i \tag{2.2}$$

The SoC (per unit) S_i at the end of each trip, including any en route charging during the trip and any parked charging immediately after the trip, is set as in the energy balance in (2.3).

$$S_i = S_{i-1} - \frac{W_i}{C} + \Pi_i \Phi_i^p(t_i^s, t_i^d, P_i^{DC}) + \Phi_i^e(S_{i-1}, \varepsilon_i) \tag{2.3}$$

where:

- C is the vehicle's battery capacity (kWh).
- Π_i is a decision variable $\{0, 1\}$ for parked charging at the end of trip i; 0 if no parked charging action taken, 1 if parked charging action taken.
- Φ_i^p is the increase in SoC from a parked charging event at the end of trip i; a function of t_i^s, the time (hours) at which the vehicle starts the parked charging event after trip i, t_i^d, the time (hours) at which the vehicle stops the parked charging event after trip i (and hence starts its next trip) and P_i^{DC}, the maximum rated DC charger power (kW) available during the parked charging event following trip i.
- Φ_i^e is the increase in SoC from en route charging events within trip i; a function of the SoC after the previous trip and any charging events during or immediately afterwards S_{i-1} and ε_i, the remaining energy requirement until the next charging

opportunity (or, if there are no charging opportunities following trip i, the end of the travel diary).

In order to schedule charging events, two further variables must be established. Firstly, S^{min} is the minimum allowable SoC (2.4) based on a prescribed minimum range r^{min} of 25 km driven at the combined energy consumption value c^c from Figure 2.3. Secondly, Z_i is the SoC after each trip i before the addition of any charging associated with that trip (2.5).

$$S^{min} = \frac{r^{min} c^c}{C} \tag{2.4}$$

$$Z_i = S_{i-1} - \frac{E_i}{C} \tag{2.5}$$

The heuristic (Figure 2.4) starts by initialising all parked charging decision variables Π_i and all increases in SoC from parked charging and en route charging Φ_i^p and Φ_i^e respectively equal to zero for all trips. The SoC at the start of the travel diary S_0 is set to 0.8 for reasons described in Section 2.1.3. The SoC S_i after each trip i – currently with no addition from charging – is calculated for all trips from (2.3). If S_i for all trips is greater than or equal to the minimum SoC S^{min}, then no charging is required. If not, parked charging events are scheduled according to the method described in Section 2.2.5. If at this point any S_i remains less than S^{min}, en route charging events are scheduled as described in Section 2.2.6.

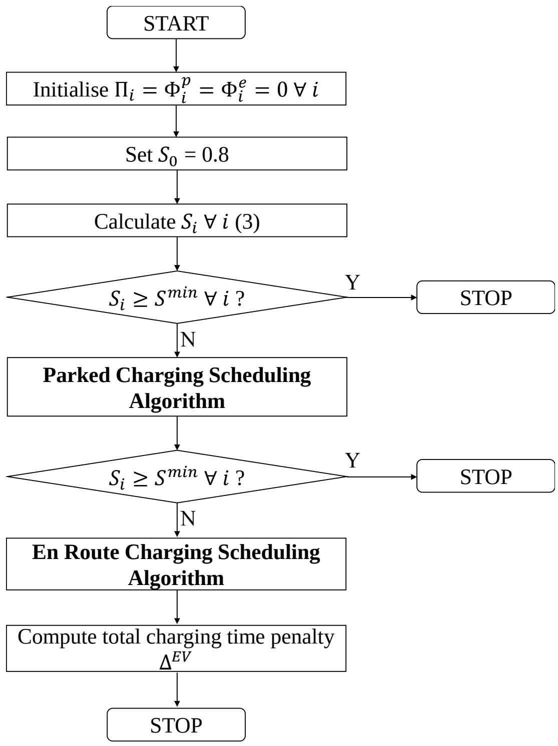

Figure 2.4: Flowchart showing heuristic method to derive idealised charging schedule given UK National Travel Survey travel diary and hence compute time penalty of charging

To illustrate the end result of the algorithm in Figure 2.4, an example charging schedule derived from the example travel diary from Table 2.1 is shown in Table 2.5 for an EV with a 24 kWh battery under the low power charging scenario with access to parked charging at home only.

Table 2.5: Example charging schedule derived using algorithm for NTS Travel Diary in Table 2.1, for EV with 24 kWh battery under the low power charging scenario with access to parked charging at home only (converter efficiency = 88%)

Trip #	**Charge Type**	**Starting SoC**	**Ending SoC**	**Rated DC power (kW)**	**Plug-in time (Weekday, HH:MM)**	**Plug-out time (Weekday, HH:MM)**
6	Home	0.34	1	3.7	Tu 12:15	Sa 07:00
9	En route	0.22	0.56	50	Su 20:12	Su 20:21
9	Home	0.22	0.8	3.7	Su 20:45	N/A

Based on the set of charging events described in Table 2.5, the total time penalty for this EV driver would be three fixed cable parked charging penalties of 17 s (Table 2.4) plus the total time of the en route charging event during trip 9, equal to 9 m 43 s. The total time penalty would therefore be 10 m 34 s. Normalised by the total time spent driving (4 h 5 m), this equates to a charging time penalty of 2 m 35 s per hour of driving.

Note that the algorithm presented in this section is also used in Chapters 4 and 5 of this thesis in order to provide a method of deriving likely charging schedules from travel diaries. Where applicable, the algorithm is modified – these modifications are described in the relevant chapters.

2.2.5 Parked Charging

Parked Charging Scheduling Algorithm

The parked charging scheduling algorithm is shown in Figure 2.5. It will first return a set $\mathcal{K}$ of trips which end with a parked charging opportunity. These are based on the destination of each trip and the level of access to parked charging that the vehicle is assumed to have (Section 2.2.2). $\mathcal{K}$ contains the indices of the trips where parked charging is possible; for example, if parked charging is possible at the end of the first, fourth and fifth trips then $\mathcal{K} = \{1, 4, 5\}$. For cases where the vehicle does not have access to any charging at the locations present in the destinations of trips in the travel diary, $\mathcal{K}$ will be an empty set and hence no parked charging events can be scheduled.

The algorithm will loop through each trip i. If $S_i < S^{min}$, then it will seek to schedule the minimum number of parked charging events before trip i such that:

1. The SoC after trip i is greater than or equal to the minimum permissible, i.e. $S_i \geq S^{min}$.

2. In a set of possible parked charging events in $\mathcal{K}$ before trip i, the one that delivers the greatest increase to S_i is chosen.

A flag variable Q is initially set to Z_i (2.5) and used to track whether taking a parked charging opportunity will lead to an improvement in S_i.

For each parked charging opportunity k in $\mathcal{K}$ that is before trip i, the potential SoC gain Φ_k^p from that opportunity is calculated. To evaluate the effect of taking a parked charging opportunity after trip k on the SoC following trip i, the decision variable is set $\Pi_k = 1$ and all other decision variables whose indices are within $\mathcal{K}$ are set to zero. The resulting value of S_i is copied as F_i and stored in $\mathcal{S}$, the set of potential values of S_i resulting from all possible parked charging opportunities before trip i.

This process is repeated until all possible parked charging events before i are trialled. If the maximum element in set $\mathcal{S}$ is greater than Q, then taking parking opportunity after trip k such that $F_k = \max(\mathcal{S})$ will offer the best improvement to the SoC after trip i out of any of those possible. In this case, the vehicle will charge while parked at the end of trip k, and the corresponding decision variable is set $\Pi_k = 1$. Once a parked charging event is chosen, it is removed from $\mathcal{K}$. S_i is updated for all trips and Q is set to S_i. This process is repeated until either $S_i \geq S^{min}$ or adding more parked charging events brings no improvement to S_i (i.e. $\max(\mathcal{S}) \leq Q$).

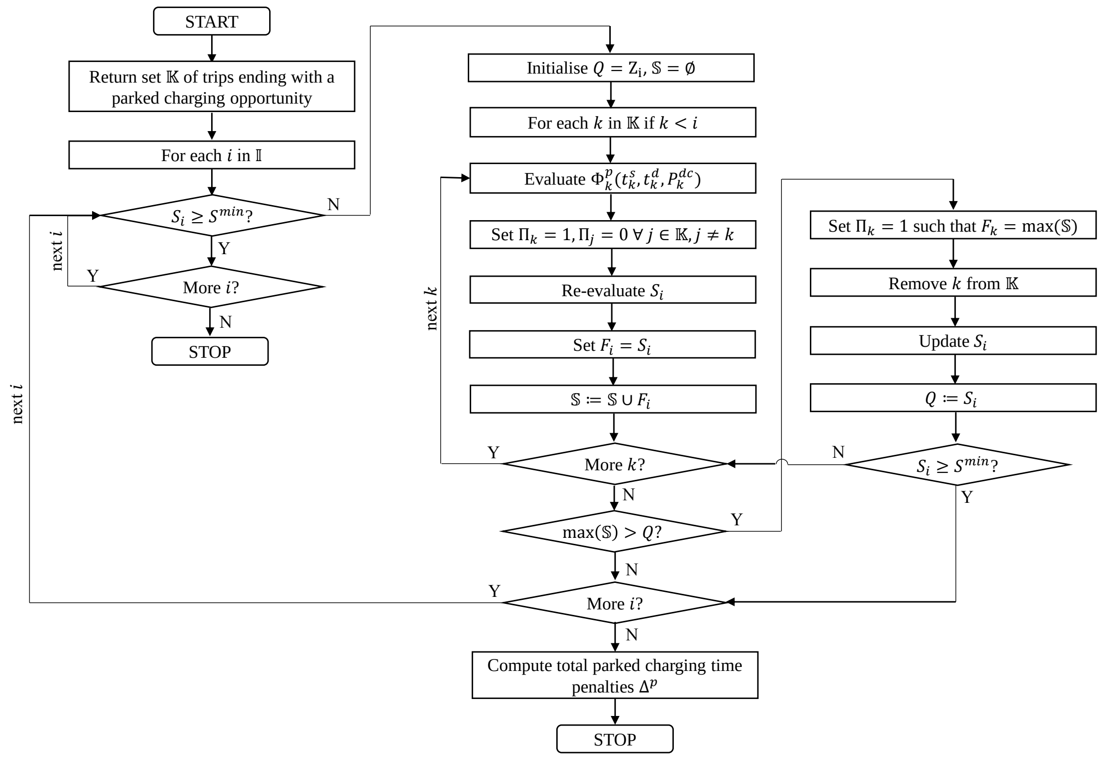

Figure 2.5: Flowchart showing parked charging scheduling algorithm

Lithium-Ion Charging Profile

Parked charging is governed by a standard Constant Current – Constant Voltage (CC-CV) lithium-ion battery charging curve [82–87] consisting of a constant current (CC) stage in which the vehicle can receive full power until its SoC reaches a value of γ, taken to be 0.8 in accordance with a real charging profile of an ABB EV charger presented in [84], followed by a constant voltage (CV) phase during which the charging power exponentially decays to zero as the SoC tends to 1. Charging power level can be expressed as a 'C-rate', i.e. the ratio of power of charging (kW) to the battery capacity (kWh). Figure 2.6 shows the charging power and SoC versus time for a battery charged at four different C-rates.

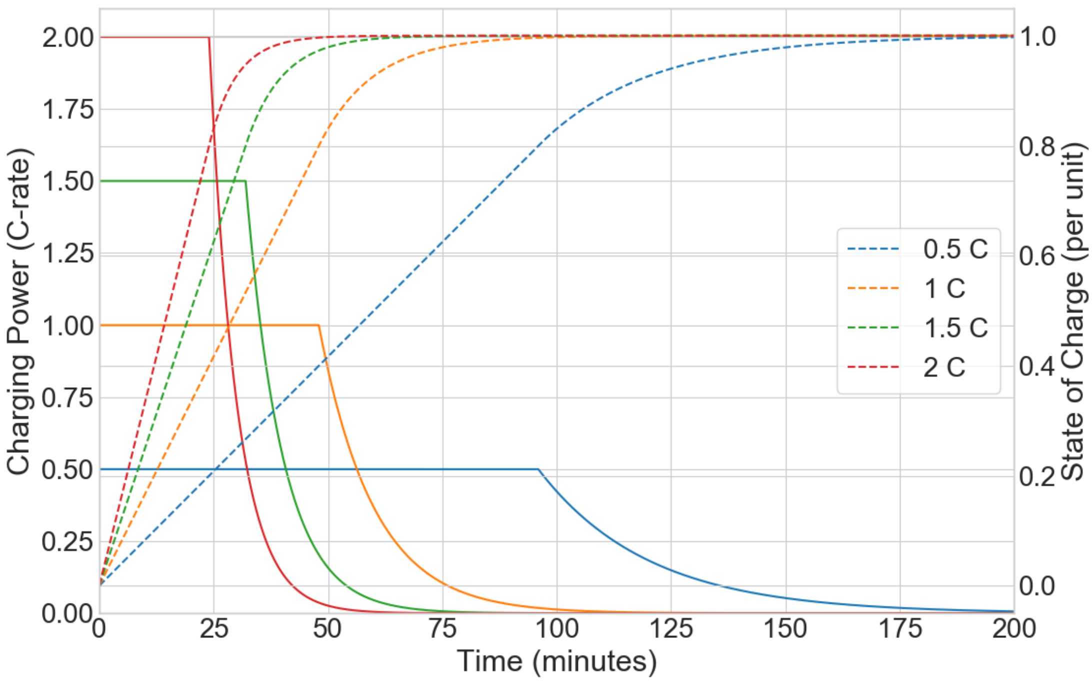

Figure 2.6: Battery charging profile for lithium-ion batteries used for simulation of charging while parked – solid lines show applied power, dashed lines show battery state of charge

The charging power (kW) of the potential parked charging event following trip i at time t (hours) is related to time via the function in (2.6).

$$P_i(t) = \begin{cases} P_i^{DC}, & t \leq t_i^{\gamma} \\ P_i^{DC} e^{-\lambda_i (t - t_i^{\gamma})}, & t > t_i^{\gamma} \end{cases} \tag{2.6}$$

where P_i^{DC} is the DC charging power (kW) available at the potential parked charging event following trip i, λ_i is the decay constant of the charger power of charging event i in the CV region and t_i^{γ} is the time (hours) in the charging event following trip i at which the battery's SoC reaches γ and the charging event transitions from the CC region to the CV region.

P_i^{DC} is equal to the corresponding AC charging power P_i^{AC} (Table 2.2) multiplied by a one-way AC/DC converter efficiency η, set to 0.88 in accordance with empirical results presented in [83] (2.7) and t_i^{γ} is calculated via linear interpolation in (2.8).

$$P_i^{DC} = \eta P_i^{AC} \tag{2.7}$$

$$t_i^{\gamma} = \frac{(\gamma - Z_i)C}{P_i^{DC}} + t_i^s \tag{2.8}$$

The type of charging event i is decided by the order of t_i^s, t_i^{γ} and t_i^d. The type of the charging event dictates how the resulting increase in SoC is calculated (Sections 2.2.5-2.2.5).

Increase in SoC due to Constant Current (CC) Only Parked Charging Events

If t_i^{γ} is greater than the parking end time t_i^d, the vehicle was not parked for sufficiently long to reach an SoC of γ and the charging event is a CC-only event. In this case, the increase in SoC from charged parking event i is calculated as in (2.9).

$$\Phi_i^{CC} = \frac{P_i^{DC}(t_i^d - t_i^s)}{C} \tag{2.9}$$

Increase in SoC due to Constant Current (CC) - Constant Voltage (CV) Parked Charging Events

If t_i^d is greater than the parking duration t_i^γ, which in turn is greater than the charging event start time t_i^s, the vehicle will be charged in CC until it reaches t_i^γ and CV thereafter. To approximate the decay constant λ_i, the area under the curve between t_i^γ and t_i^∞, the time at which the charging power reaches a value close to zero (taken as 1% of the maximum rated power P_i^{DC}), must be equal to 20% of the battery's capacity C (2.10).

$$\int_{t_i^\gamma}^{t_i^\infty} P_i^{DC} e^{-\lambda_i(t-t_i^\gamma)} dt = 0.2C \tag{2.10}$$

After performing the integration and simplifying, an expression in terms of λ_i and t_i^∞ results in (2.11).

$$P_i^{DC}(e^{-\lambda_i(t_i^\infty - t_i^\gamma)} - 1) + 0.2C\lambda_i = 0 \tag{2.11}$$

For a given charging power, λ_i and t_i^∞ are approximated by the solution of a multivariate optimisation problem: to minimise the objective function expressed in (2.12) subject to the constraints in (2.13)-(2.15).

$$f(\lambda_i, t_i^\infty) = P_i^{DC}(e^{-\lambda_i(t_i^\infty - t_i^\gamma)} - 1) + 0.2C\lambda_i \tag{2.12}$$

$$f(\lambda_i, t_i^\infty) \geq 0 \tag{2.13}$$

$$\lambda_i, t_i^\infty > 0 \tag{2.14}$$

$$e^{-\lambda_i(t_i^\infty - t_i^\gamma)} < 0.01 \tag{2.15}$$

The total energy transferred to the vehicle's battery in the CV region is found by evaluating the integral on the LHS of (2.10) between t_i^γ and t_i^∞. This allows the calculation of the increase in SoC from a CC-CV parked charging event (2.16).

$$\Phi_i^{CC-CV} = \frac{P_i^{DC}(t_i^{\gamma} - t_i^s) + \frac{P_i^{DC}}{\lambda_i}(1 - e^{-\lambda_i(t_i^{\infty} - t_i^{\gamma})})}{C} \tag{2.16}$$

Increase in SoC due to Constant Voltage (CV) Only Parked Charging Events

If t_i^s is greater than t_i^{γ}, the vehicle began the charging event with an SoC above γ. In this case, the total energy transferred to the vehicle's battery in the CV region is found by evaluating the integral on the LHS of (2.10) between t_i^s and t_i^{∞}. Simplifying, this gives the calculation of the increase in SoC from a CV-only parked charging event as (2.17).

$$\Phi_i^{CV} = \frac{P_i^{DC}}{\lambda_i e^{-\lambda_i t_i^{\gamma}}}\left(e^{-\lambda_i t_i^s} - e^{-\lambda_i t_i^{\infty}}\right) \tag{2.17}$$

Selection of SoC Increase Function

The SoC increase function due to parked charging event i is given by (2.18).

$$\Phi_i^p = \begin{cases} \Phi_i^{CC}, & t_i^s < t_i^d \leq t_i^{\gamma} \\ \Phi_i^{CC-CV}, & t_i^s < t_i^{\gamma} \leq t_i^d \\ \Phi_i^{CV}, & t_i^{\gamma} \leq t_i^s < t_i^d \end{cases} \tag{2.18}$$

The time penalties due to parked charging δ_i^p (hours) for each trip i in a vehicle's travel diary are found by (2.19).

$$\delta_i^p = \begin{cases} \delta_i^{fp}, & \Pi_i = 1 \\ 0, & \text{otherwise} \end{cases} \tag{2.19}$$

where δ_i^{fp} is a fixed charging time penalty (hours) that depends on the location of charging (Section 2.2.3).

2.2.6 En Route Charging

En Route Charging Scheduling Algorithm

En route charging events are scheduled only if $S_i < S^{min}$ for any trip following the scheduling of parked charging events as in Section 2.2.5. The algorithm used for scheduling en route charge events is shown in Figure 2.7.

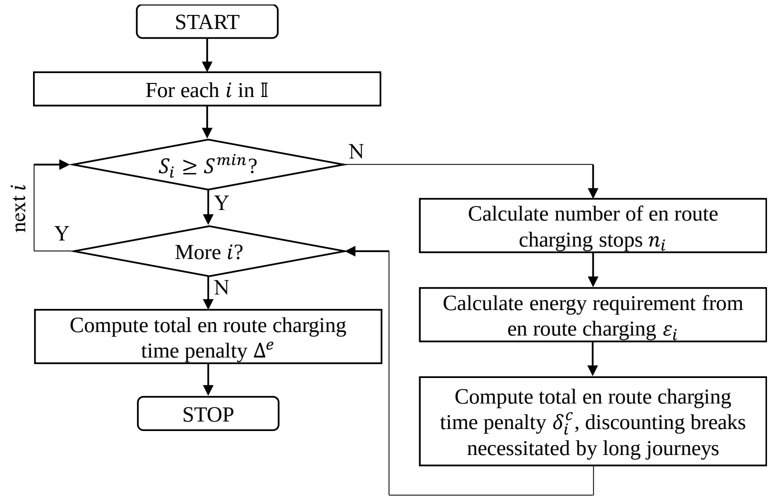

Figure 2.7: Flowchart showing en route charging scheduling algorithm

Increase in SoC from En Route Charging Events

Upon discovery of a trip for which $S_i < S^{min}$, the algorithm will calculate the number of necessary en route charging stops n_i during that trip (2.20). The numerator in (2.20) represents the energy that the vehicle must attain in en route charging events to make it to the end of trip i with an SoC equal to S^{min}. This is given by the energy requirement of trip i minus the 'free energy' the vehicle has at the beginning of trip i, i.e. the difference between S_{i-1} and S^{min} multiplied by the battery capacity C. The denominator in (2.20) represents the maximum quantity of energy that can be taken by the vehicle in one charge: as charging from 80% to 100% SoC would take a disproportionately long time (Section 2.2.5), the vehicle will stop charging when it reaches 80% SoC. It should be noted that while this assumption is valid for the CC-CV charging profile as shown in Figure 2.6, the advent of charging techniques such as the sinusoidal-ripple-current proposal in [88], the fuzzy multi-stage approach in [89], the SoC estimation method in [90] or the multi-stage CC-CV method in [91], has the potential to allow EVs to charge to SoCs above 80% in significantly less time than it would take for a typical CC-CV regime such as in Figure 2.6. Under such a regime, the denominator in (2.20) would increase and drivers would be able to receive a greater amount of energy from a given en route charging session. The effect of this would be to reduce the level of charging inconvenience suffered by drivers, as they would have to make fewer stops.

$$n_i = \begin{cases} \left\lceil \dfrac{E_i - (S_{i-1} - S^{min})C}{(\gamma - S^{min})C} \right\rceil, & \text{if } E_i > (S_{i-1} - S^{min})C \\ 0, & \text{otherwise} \end{cases} \tag{2.20}$$

If trip i does not present the vehicle with a parked charging opportunity, then it will charge more than is required for the current trip, up to a limit of 80% SoC on the final (n_i^{th}) en route charging session in trip i, so as to avoid having to charge immediately upon starting the next trip. Any further charging requirement until the next parked charging opportunity (denoted by trip o in (2.21)) will be covered in subsequent trips. It follows that the energy requirement ε_i for all en route charging sessions in trip i is given by (2.21).

$$\varepsilon_i = \begin{cases} \min \{ n_i(\gamma - S^{min})C - (S_{i-1} - S^{min})C, \\ \displaystyle\sum_{h=i}^{o} E_h - (S_{i-1} - S^{min})C \}, & \text{if } n_i \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{2.21}$$

The SoC increase due to all en route charging events in trip i, Φ_i^e, is then given by (2.22).

$$\Phi_i^e = \frac{\varepsilon_i}{C} \tag{2.22}$$

Calculation of En Route Charging Time Penalties

It follows that the time penalty δ_i^e (hours) endured by the vehicle from the en route charge events in trip i is a sum of the fixed charging time penalties δ_i^{fe} (hours) associated with plugging in and removing the cable (Section 2.2.3) and the total en route charging duration δ_i^c (hours) (2.23), which is adjusted to account for the presence of any natural breaks that would have been taken as part of long journeys as per Section 2.1.3 (2.24).

$$\delta_i^e = n\delta_i^{fe} + \delta_i^c \tag{2.23}$$

$$\delta_i^c = \begin{cases} \dfrac{\varepsilon_i}{P^e} - 0.25\left\lfloor \dfrac{D_i}{h} \right\rfloor, & \text{if } \dfrac{\varepsilon_i}{P^e} > 0.25\left\lfloor \dfrac{D_i}{h} \right\rfloor \\ 0, & \text{otherwise} \end{cases} \tag{2.24}$$

where P^e is the en route charging power available, depending on the battery capacity and charging power scenario (Table 2.2), and h is the number of hours' driving before a 15 minute (or 0.25 hour) break is necessitated. In the UK Highway Code compliant scenario, $h = 2$. In the sensitivity case, $h = 4$.

2.2.7 Boundary Conditions

As mentioned in Section 2.1.3, the EV must finish its travel diary with an SoC of γ, so as to have replenished all the energy it expended through making the series of trips. If the travel diary's final trip represents a charging opportunity, then a fixed time penalty associated with plugging in and removing the cable is applied according to the type of parked charging event it is (Table 2.4). If not, then the parked charging scheduling algorithm (Section 2.2.5) is run to find the minimum number of parked charging events such that the final SoC is at least γ. If it is still below γ, then an en route charging session must be scheduled (Section 2.2.6) and the corresponding time penalties are added to the vehicle's total.

2.2.8 Total EV Charging Time Penalty

The total charging time penalty seen by an EV given a travel diary Δ^{EV} is given by (2.25).

$$\Delta^{EV} = \sum_{i \in \mathcal{I}} (\delta_i^e + \delta_i^p) \tag{2.25}$$

The results presented in Section 2.3 are normalised by the total driving time in the vehicle's travel diary to give $\hat{\Delta}^{EV}$ in minutes time penalty per hour of driving time, hence allowing easier comparison across the spectrum of driving behaviours (2.26).

$$\hat{\Delta}^{EV} = \frac{60\Delta^{EV}}{\sum\limits_{i \in \mathcal{I}} D_i} \tag{2.26}$$

2.2.9 Comparison to ICV Fuelling

Overview

An ICV's fuelling time penalty is equal to a fixed time penalty associated with a fuelling action from a minimum fuel level (at which the vehicle's remaining range is 25 km) to a full tank multiplied by the amount of fuel the vehicle consumes during the week as a proportion of a the fuel tank's usable space.

Fixed Fuelling Time Penalty

Two ICVs were used for the comparative analysis to represent a likely spread of the expected time penalty of ICV fuelling; the 2018 Fiat 500 1.4L petrol, a small 'city' car with a 40 litre fuel tank and a fuel economy of 11.9/12.8/14.0 km/l (city/combined/highway) and the 2018 Kia Sorento 2.4L petrol, a larger, longer-range vehicle with a 71 litre fuel tank and a fuel economy of 8.9/9.4/10.6 km/l (city/combined/highway). As for the EV analysis, the fuel economy data was taken from the US Environmental Protection Agency's fuel economy test data [38].

The time penalty of a fuelling stop was fixed, based on the observed time taken for 50 ICVs visiting a petrol station in Glasgow, UK. The total time to visit the petrol station was taken as the time between stopping at the pump and leaving the pump after refuelling. Figure 2.8 shows histograms and CDFs for the time taken to refuel an ICV, the time taken to pay for the fuel either in the shop or at the pump and the total time between arriving at the pump and leaving again after refuelling, including any walking between the car, pump and shop.

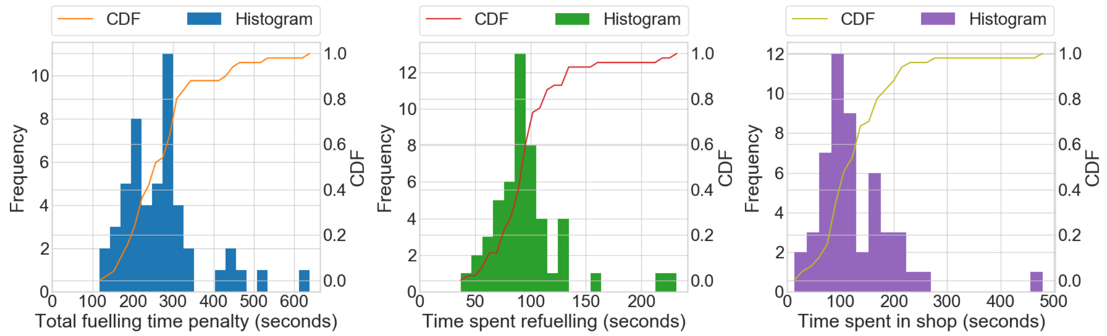

Figure 2.8: Probability distributions of time taken to refuel ICV at a petrol station, comprising of time taken to refuel and time taken for fuel payment

It was found that the mean time taken to refuel an ICV was 271 seconds, comprised of 97 seconds pumping fuel into the vehicle, 126 seconds paying for the fuel either in the shop or at the pump and the remaining 48 seconds walking between the car, pump and shop. As could be expected, Figure 2.8 shows a greater variation in the time spent paying for the fuel than in the time spent actually fuelling the vehicle, likely because customers could have been buying other items or subject to a queue within the shop.

Due to its considerably larger fuel tank size, the Kia Sorento is subject to fewer petrol station stops than the Fiat 500. To establish a spread of expected petrol station time penalties, the best case is represented by the Kia Sorento with a fuelling time penalty of 207 seconds and the worst case is represented by the Fiat 500 with a fuelling time penalty of 294 seconds, representing the 25^{th} and 75^{th} percentiles respectively of the total time spent at the petrol station (Figure 2.8). Note that although these time penalties are given in seconds, they are converted to hours for all equations presented in this chapter.

Although the time taken for the driver to get out of and re-enter the vehicle is not included in the fixed EV charging time penalties (Section 2.2.3), it is included in the

ICV fuelling time penalty. This is based on the assumption that, unlike in a parked EV charging event, the driver is not leaving the car for any other reason than to refuel. Furthermore, unlike an en route EV charging event, the time taken to exit and re-enter the vehicle is not negligible in comparison to the total fuelling time penalty. It is assumed that the time spent driving up to the petrol pump or the EV charge point is common to both ICV fuelling and EV charging and would vary based on the specific EV charging station or petrol station: thus, it is not included in either case.

Calculation of Time Penalty from ICV Fuelling Given a Travel Diary from the UK National Travel Survey

For each trip i in the travel diary, the fuel requirement f_i (l) is (2.27).

$$f_i = \frac{d_i}{\epsilon_i} \tag{2.27}$$

where d_i and ϵ_i are the distance (km) and fuel economy (km/l) of each trip. The fuel economy levels (city/combined/highway) are set by trip according to the same speed thresholds as in the EV analysis (Section 2.2.4).

The minimum level of fuel the vehicle f^{min} is permitted is the amount of fuel that would deliver the prescribed minimum range r^{min} of 25 km based on the combined fuel economy ϵ^c (2.28), as analogous to the EV analysis (2.4).

$$f^{min} = \frac{r^{min}}{\epsilon^c} \tag{2.28}$$

The time penalty δ_i^{ICV} (hours) associated with trip i is then the fixed fuelling time penalty δ^{fuel} (hours) multiplied by the fuel requirement f_i as a proportion of the usable fuel tank space (given between the difference between the tank size V (l) and the minimum fuel f^{min}). As with the EV analysis, any natural breaks taken as a result of long journeys are accounted for (2.29).

$$\delta_i^{ICV} = \begin{cases} \delta^{fuel} \dfrac{f_i}{V - f^{min}} - 0.25 \left\lfloor \dfrac{D_i}{h} \right\rfloor, & \text{if } \delta^{fuel} \dfrac{f_i}{V - f^{min}} > 0.25 \left\lfloor \dfrac{D_i}{h} \right\rfloor \\ 0, & \text{otherwise} \end{cases} \tag{2.29}$$

As the time penalty of fuelling an ICV is much shorter and the ranges of the vehicles are longer, there is no reported difference in the resulting fuelling time penalty between the Highway Code compliant case and the sensitivity case.

The total fuelling time penalty over the course of a travel diary Δ^{ICV} is then the sum of the fuelling time penalties over the set of trips $\mathcal{I}$ (2.30) which, as in the EV analysis, is normalised by the total time spent driving to give $\hat{\Delta}^{ICV}$ (2.31).

$$\Delta^{ICV} = \sum_{i \in \mathcal{I}} \delta_i^{ICV} \tag{2.30}$$

$$\hat{\Delta}^{ICV} = \frac{60\Delta^{ICV}}{\sum_{i \in \mathcal{I}} D_i} \tag{2.31}$$

2.3 Results

2.3.1 Total Charging Time Penalty per Driving Time

Cumulative Distribution Functions

Due to the significant variation in the duration and distance of journeys made across the 39,020 travel diaries for which charging schedules are derived, results are presented in the form of cumulative distribution functions (CDFs) in Figures 2.9-2.12 for four scenarios relating to the charging power available (Section 2.2.2) and the breaks taken during long journeys scenario (Section 2.1.3). Each figure shows a plot for each battery capacity trialled. In all plots, the vertical axis shows the proportion of travel diaries whose total normalised charging time penalty (minutes per hour driving) is less than or equal to the corresponding horizontal axis value. Two lines are shown on each plot for a direct comparison to the fuelling time penalty endured by ICVs for the 'worst case' (Fiat 500, 75^{th} quartile refuel time) and the 'best case' (Kia Sorento, 25^{th} quartile refuel time) (Section 2.2.9). The level of charging access is given in the legends: H, W and P represent access to home, work and public destination charging respectively and a ¬ symbol preceding any letter represents lack of access to charging at that location. The horizontal axes are limited to values below 5 minutes' charging time penalty per hour driving to enable clarity for lower charging time penalties.

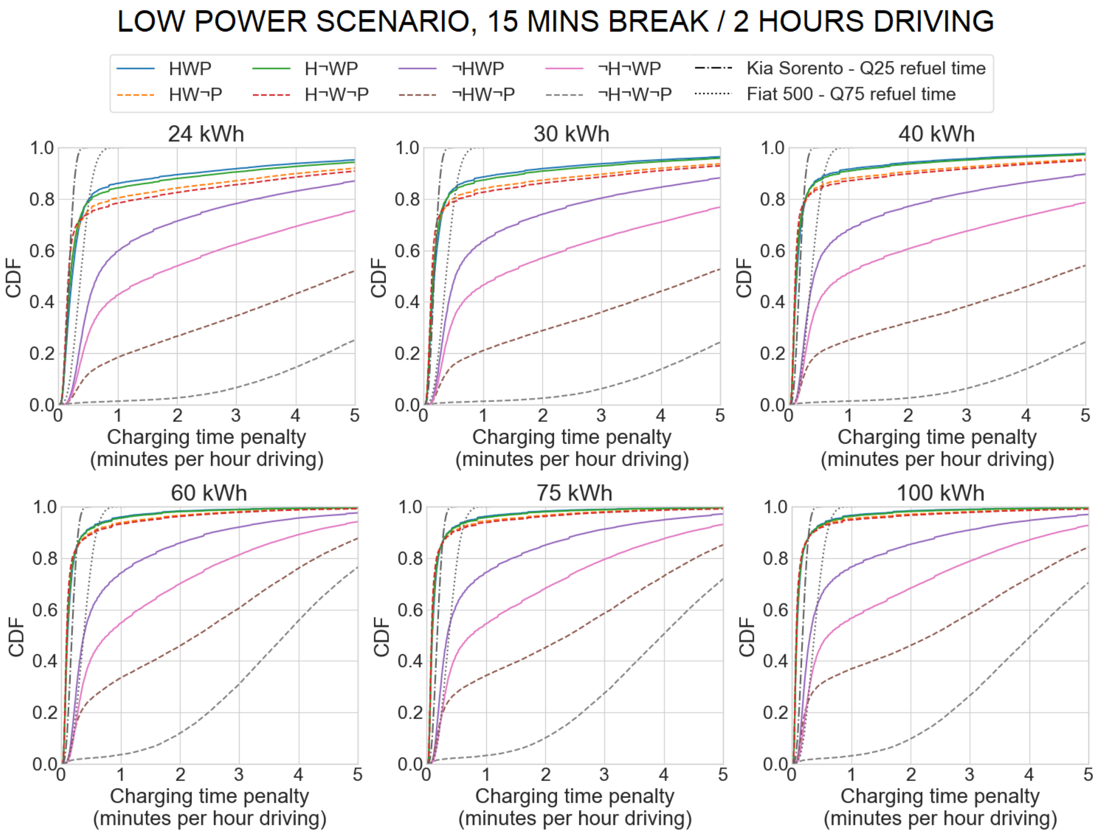

Figure 2.9: Cumulative distribution functions of normalised charging time penalty (minutes per hour driving) for various battery capacities and levels of charging access – low power scenario, UK Highway Code compliant case (15 minutes' break per 2 hours' driving)

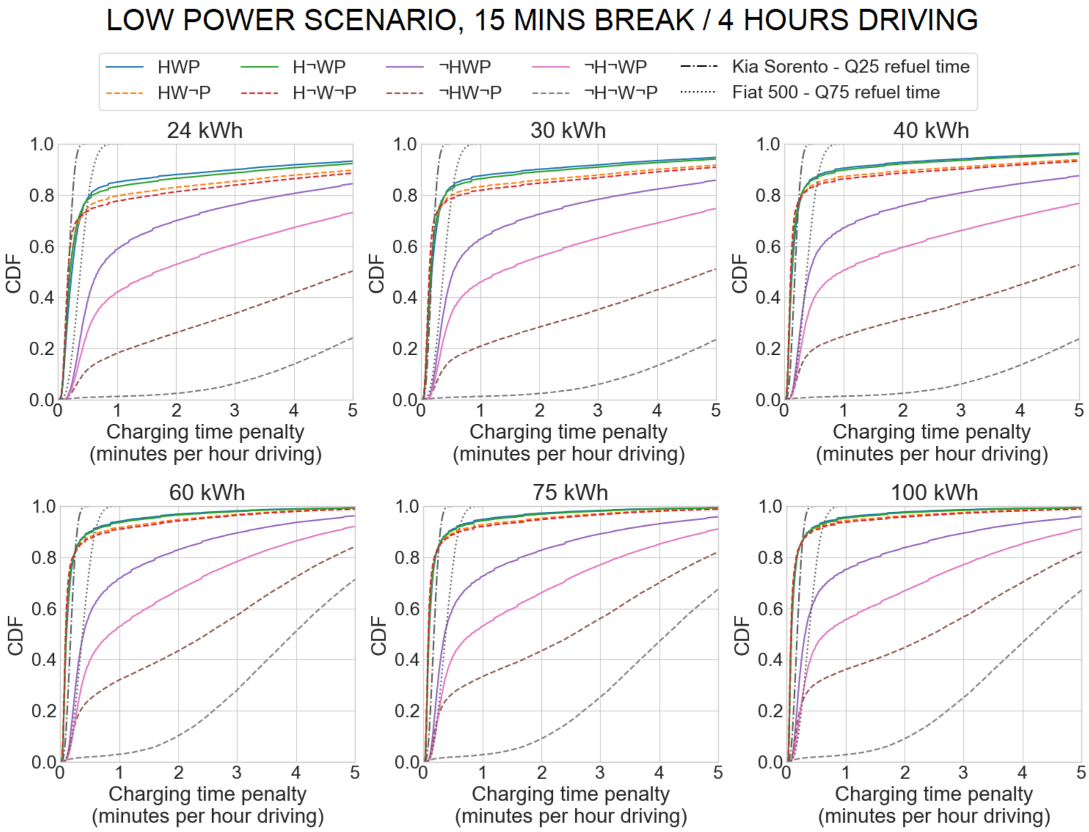

Figure 2.10: Cumulative distribution functions of normalised charging time penalty (minutes per hour driving) for various battery capacities and levels of charging access – low power scenario, sensitivity case (15 minutes' break per 4 hours' driving)

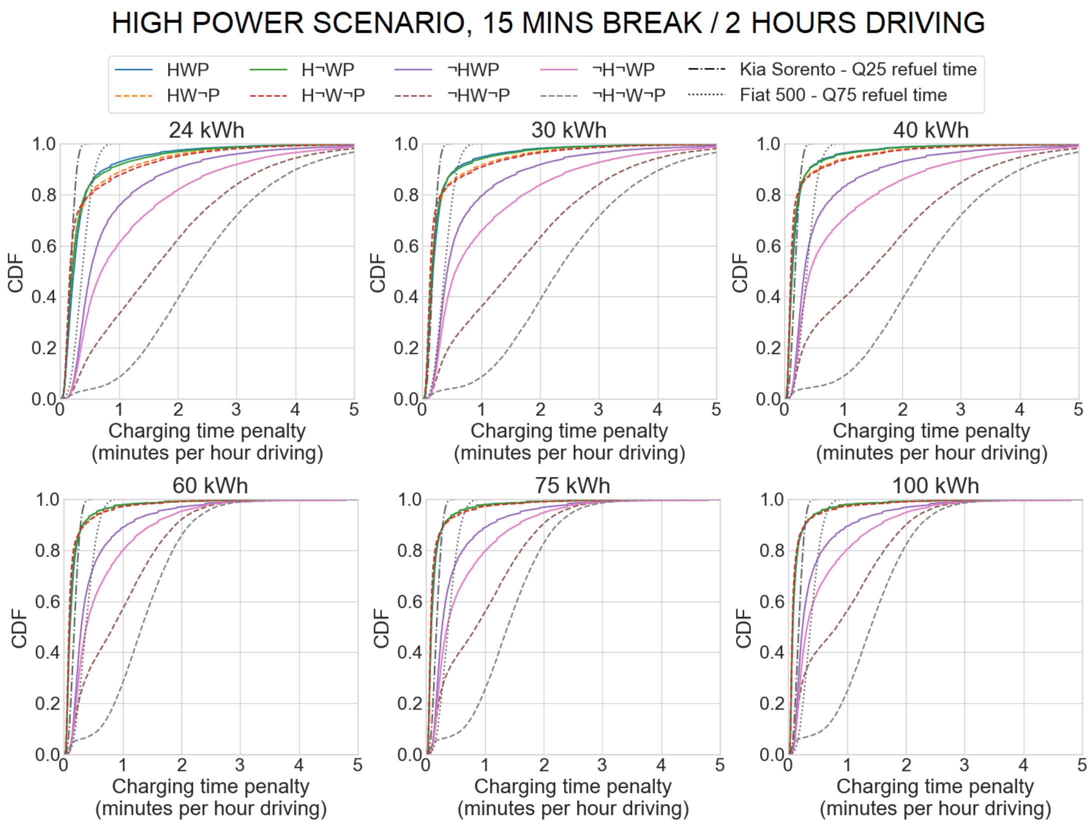

Figure 2.11: Cumulative distribution functions of normalised charging time penalty (minutes per hour driving) for various battery capacities and levels of charging access – high power scenario, sensitivity case (15 minutes' break per 2 hours' driving)

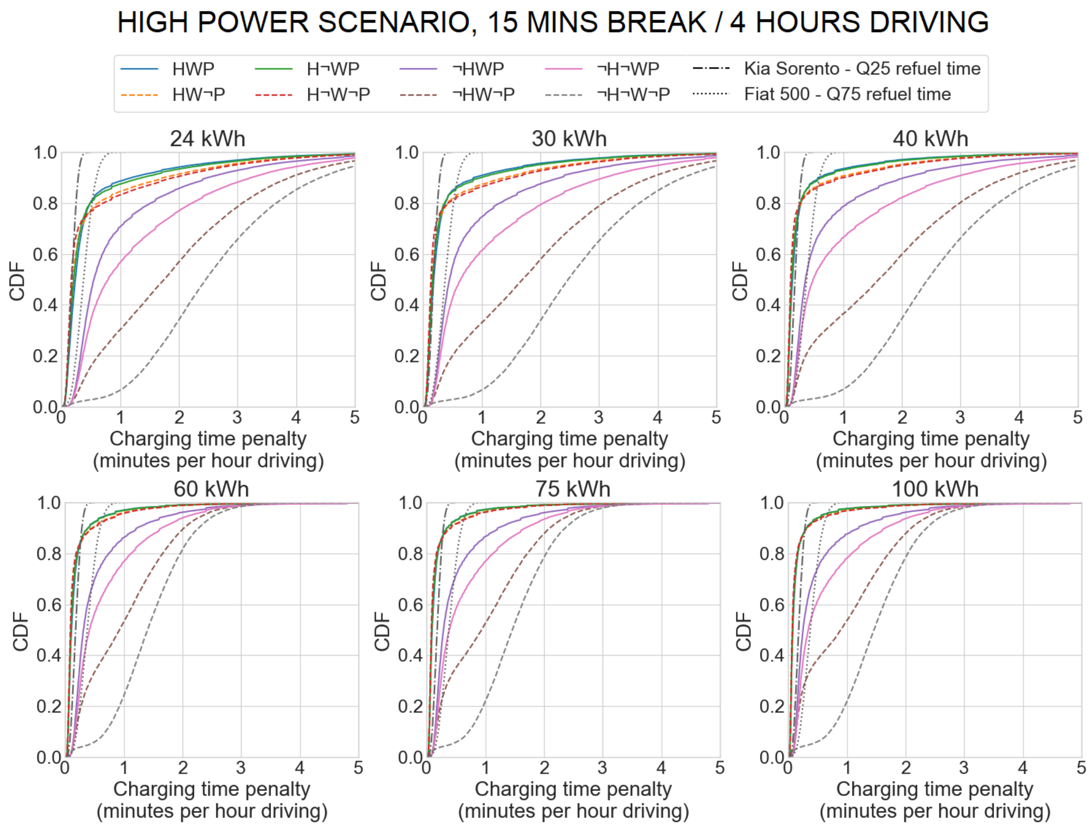

Figure 2.12: Cumulative distribution functions of normalised charging time penalty (minutes per hour driving) for various battery capacities and levels of charging access – high power scenario, sensitivity case (15 minutes' break per 4 hours' driving)

Despite the normalisation of the results in terms of charging time penalty per driving time, Figures 2.9-2.12 show a significant variation in the total charging time penalty per driving time experienced by would-be EV drivers using the synthesised NTS travel diaries. This is due to the variation in the type of journeys individuals are making, particularly in terms of distance (and therefore energy requirement) and the frequency and duration of parking opportunities between journeys. The variation in EV charging time penalty is shown to be significantly greater than the variation in ICV fuelling time penalty. This is due to the different types of time penalties involved; where drivers are forced to charge en route, their time penalty is much greater than if they are not.

Having access to charging at more locations is shown to significantly reduce the time penalty that an EV driver will expect to endure, with access to home charging being far more useful for minimising the total time penalty than workplace or public destination charging. Consider the results for the low power charging scenario/Highway Code Rule 91 compliant case with 24 kWh batteries as an example (the top-left plot in Figure 2.9): while only a small proportion (1.31%) of EVs that rely solely on en route charging (¬H¬W¬P) would endure a charging time penalty of a minute or less per hour of driving, this is increased to 78.3% for EVs who have access to charging at home but nowhere else (H¬W¬P) and 86.0% for EVs who have access to charging at all three options (HWP).

Increasing the battery capacity also offers a dramatic reduction in time penalty, providing the vehicle has some level of access to parked charging. Considering the same set of results (Figure 2.9), the 78.3% of EVs with 24 kWh batteries and H¬W¬P access to charging that expect to endure less than a minute of charging time penalty per hour driving becomes 87.0% for 40 kWh batteries and 94.8% for 100 kWh batteries; the 86.0% of EVs with 24 kWh batteries and HWP access to charging that expect to endure less than a minute of charging time penalty per hour driving becomes 91.6% for 40 kWh batteries and 96.6% for 100 kWh batteries. For individuals who solely rely on en route charging, the effect of increasing the battery size (and therefore the range), results in fewer stops and therefore fewer fixed time penalties. However, the expended energy must still be recouped after the travel diary so the time penalty associated with en route charging itself must be the same for a given charging power. The result is a very slight increase in the proportion of EVs that expect to endure a charging time penalty of a minute or less per hour of driving from 24 kWh (1.31%) to 40 kWh (1.34%), and a larger increase for when vehicles have access to higher charger power, as they are assumed to for capacities of 60 kWh and over (Table 2.2) – accordingly, 3.1% of EVs with 100 kWh batteries are expected to endure a charging time penalty of a minute or less per hour of driving.

By comparing Figures 2.9 and 2.11, the effect of charging power is shown for the UK Highway Code compliant assumption. The result of increasing charging power from the low to high power scenario is a reduction in time penalty for all use cases, though a much greater reduction for those without access to charging at home due to the greater increases in charging power as a result of moving from the low to high power charging scenarios (Table 2.2) and the fact that EV users who lack access to charging at home are more likely to be forced to rely on en route charging to a greater extent, something which carries a time penalty associated with the charging itself, which is inversely proportional to the charger power available. For example, while 20.9% of 30 kWh EVs would experience a charging time penalty of a minute or less with ¬HW¬P under the low power scenario, 35.9% of the same EVs would experience the same time penalty or less under the high power scenario.

The effect of increasing charging power is greater for those with higher time penalties than it is for those with lower time penalties. This is because those with higher penalties are increasingly dominated by en route charging which, as already mentioned, carries a time penalty inversely proportional to the charging power. This can be seen by comparing Figures 2.9 and 2.11; whereas in the low power scenario there remains a small proportion of EVs with 24, 30 or 40 kWh batteries with access to charging at home who are expected to endure a time penalty of greater than 5 minutes per hour of driving, for the high power charging scenario virtually 100% of EVs of all battery sizes can expect to endure a charging time penalty of less than 3 minutes per hour of driving.

By comparing Figure 2.9 with Figure 2.10 and Figure 2.11 with Figure 2.12, the effect of moving from the Highway Code compliant case to the sensitivity case is to reduce the cumulative probabilities that a vehicle will experience a normalised time penalty under a certain value. Though slight, the effect is more pronounced at larger normalised time penalties, reflecting the fact that those more likely to endure greater time penalties (chiefly diaries with longer journeys and therefore a need to stop and charge en route) are more likely to be affected by this assumption.

Convenience Parity between EVs and ICVs

'Convenience parity' is defined in this chapter as the point – for a particular combination of battery capacity, charger power and level of access to charging – at which EV charging carries a comparable time penalty to ICV fuelling. Convenience parity is shown in Figures 2.9-2.12 by the region where the coloured lines representing the time penalty endured by EVs under each case are between the black lines representing the best and worst cases for ICV fuelling.

As suggested in Section 2.1.1, there could be cases where EV charging is of greater convenience than ICV fuelling, provided that parked charging opportunities (which have a smaller time penalty than ICV fuelling events) are sufficiently plentiful such that the vehicle does not run out of range between them. This is indicated by the regions in Figures 2.9-2.12 by the coloured lines being to the left of the black lines: for example, in the low power, UK Highway Code compliant case (Figure 2.9), it is clear than approximately 80% of EVs with 40 kWh batteries would expect less inconvenience than ICV users if they had access to charging at home. This is a particularly significant result as 40 kWh has recently established itself as a ‘standard’ battery capacity for EVs at the affordable end of the market (this is discussed further in Section 2.4). The effect of charger power on the proportion of EVs that are likely to experience greater convenience than ICVs is negligible. This is due to the fact that those with low time penalties are dominated by fixed time penalties associated with plugging in/removing cables and hence are not affected by charging power. It should be noted that there are no combinations of battery size and charger power that allow EVs without access to home charging greater convenience than ICVs.

In the low power charging scenario for those with access to at least charging at home, in excess of 75% of travel diaries achieved convenience parity from battery sizes of 24 kWh, increasing to 85% for battery sizes of 40 kWh and 90% for 60 kWh. Convenience parity is significantly more difficult to achieve without access to charging at home. The next best option is shown to be having access to charging at both work and public places. This enables convenience parity for approximately 50% of travel diaries with battery capacities of 40 kWh.

Increasing the charging power makes it easier for convenience parity to be achieved for those without access to charging at home; in a high power scenario, around 60% of 40 kWh EVs with access to charging at work and public places can expect convenience parity with ICVs. However, a sizeable proportion of EV drivers can still expect to see considerable inconvenience relative to ICV drivers: even with large battery sizes, only a small proportion of travel diaries were able to achieve convenience parity between EVs and ICVs.

A common factor to all plots in Figures 2.9-2.12 is the trend towards significantly larger time penalties expected for those who must rely solely on en route charging. Due to the boundary conditions assumption detailed in Section 2.1.3, the time penalty expected by these individuals does not change with battery size, apart from the fact that the highest three battery sizes on trial are assumed to have access to a faster rate of charging (Table 2.2). An increase in charger power reduces the time penalty suffered by this group of individuals, though there is no combination of battery capacity or charger power that enables their convenience parity with ICVs: due to the significant difference in the rate at which energy can be added to the vehicle based on current battery technology (as previously discussed in Section 2.1.1), the use of an EV will remain considerably less convenient than the use of an ICV unless the driver has some level of access to parked charging.

2.3.2 Delay due to Charging During Long Journeys

Proportion of Trips Facing Delay due to Charging

Figure 2.13 shows a histogram of all journeys in the NTS data by distance, with vertical lines to indicate the proportion of journeys that could not be completed on a single charge with at least 25 km range remaining, given the journeys' energy requirements and vehicles' energy consumption levels (Figure 2.3).

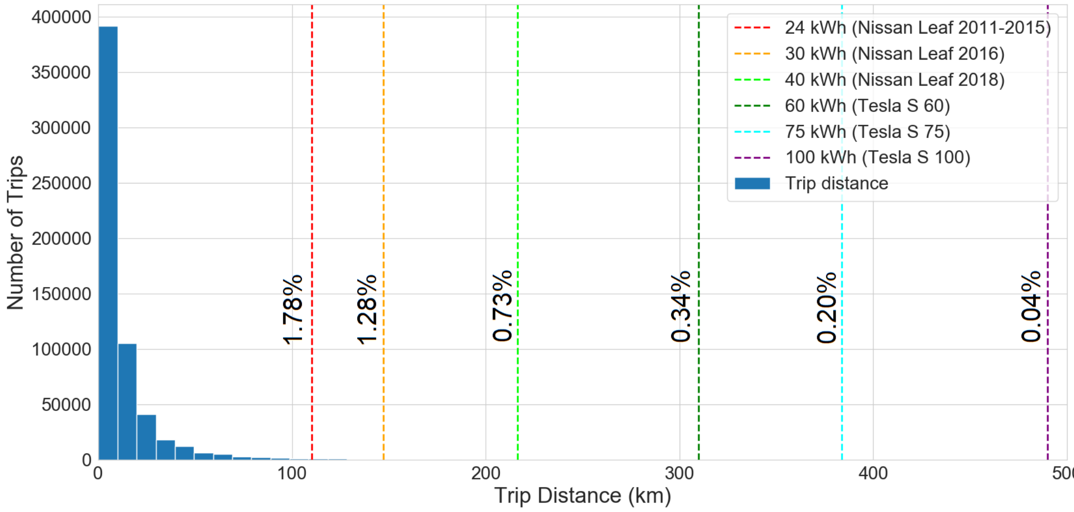

Figure 2.13: Histogram showing frequency of trips in UK National Travel Survey by distance with vertical lines indicating the proportion of trips that each vehicle modelled would not be able to complete on a single charge with at least 25 km range remaining

While the proportion of trips that are outside of the range of all vehicles considered could be stated as being relatively small, the perception that EV charging would cause an inconvenience during long journeys has already been discussed as a barrier preventing consumers switching their ICVs for EVs.

Figure 2.14 shows a breakdown of the proportion of trips which would face a delay from having to charge where the charging could not be fitted into the natural breaks taken during the journeys for varying battery capacities if it is assumed UK Highway Code Rule 91 is followed (left) and for the sensitivity case where drivers take breaks half as often as they are advised to (right). Note that for the analysis presented in this section, it is assumed that the vehicle starts each long journey with an SoC of 1.

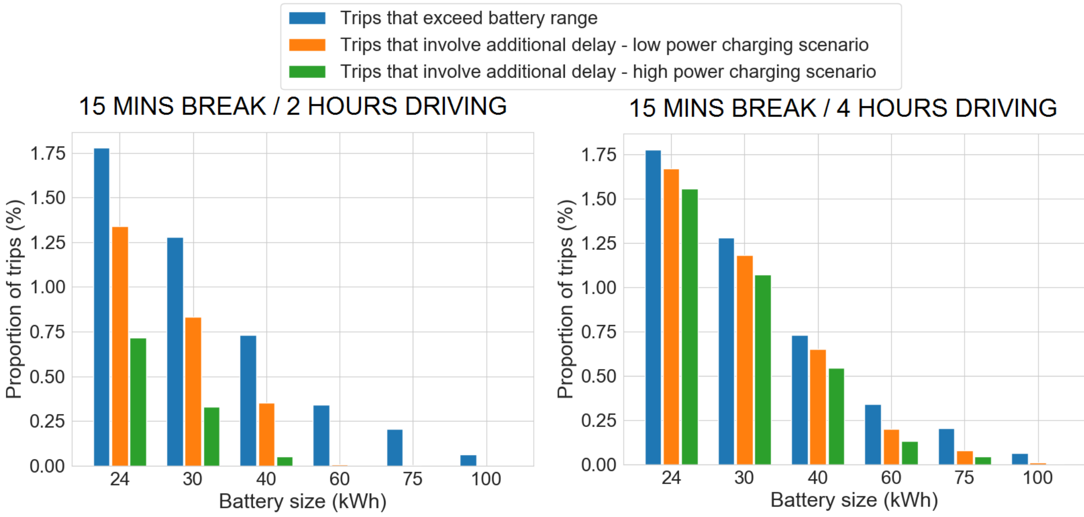

Figure 2.14: Proportion of trips facing delay for EVs with various battery sizes for low and high power charging scenarios – UK Highway Code Rule 91 case (left) and sensitivity case (right)

In Figure 2.14, the blue bars represent the vertical lines as on Figure 2.13 and the orange/green bars represent the proportion of journeys that would be delayed by charging over and above the delays for natural breaks. As shown by the difference between the orange and green bars, increasing the charging power available to the vehicle reduces the proportion of trips that incur a delay additional to that for natural breaks. Drivers who take fewer breaks than recommended by the Highway Code will experience more frequent additional delays for charging. Due to the higher charging power available for EVs with battery capacities of 60 kWh and above, the proportional difference between the blue bars and other bars is greater for these larger battery sizes: for the case where drivers are compliant with the UK Highway Code, 0.007% of journeys are expected to face delay due to charging for an EV with a 60 kWh battery for the low power charging scenario, that result being 0.0002% for the high power charging scenario. For the sensitivity case, this is significantly higher: 0.21% of journeys are expected to face a delay for the low power charging scenario and 0.12% of journeys are expected to face a delay under a high power charging scenario.

Adjusted Journey Times due to Charging Delay

Figure 2.15 presents probability distributions of the length of delay that EV drivers can expect on long journeys for different battery capacities for the low power (left) and high power (right) charging scenarios for both the Highway Code Rule 91 case (top) and the sensitivity case (bottom).

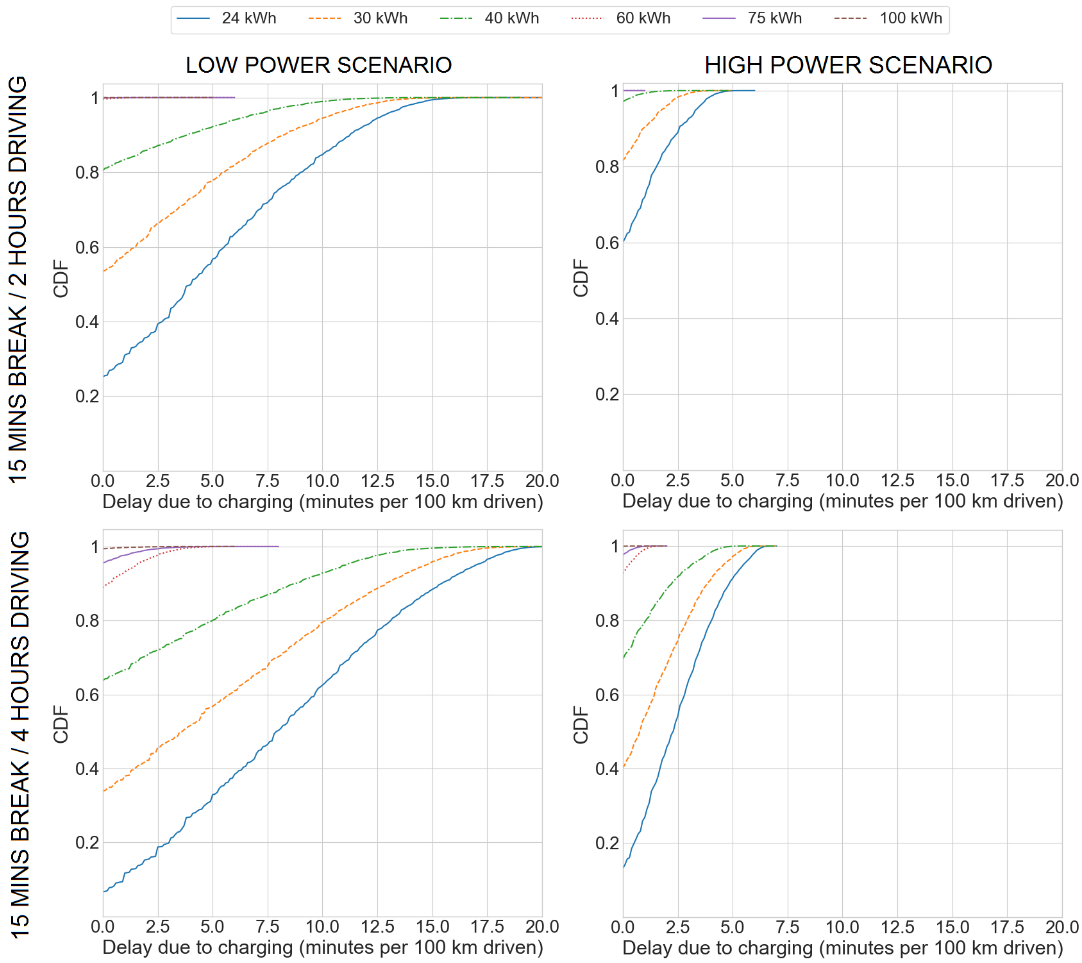

Figure 2.15: Cumulative distribution functions showing the length of delay due to charging per 100 km driving distance for various battery sizes for low power (left) and high power (right) charging scenarios for both the Highway Code Rule 91 case (top) and the sensitivity case (bottom)

Figure 2.15 shows that on the occasions when delays do occur, their duration is linked to battery capacity and charging power. To consider the case where drivers are assumed to be compliant with the UK Highway Code: while approximately 45% of journeys with a 24 kWh EV that faced a delay would experience a delay exceeding 5 minutes per 100 km driven, approximately 10% of journeys with a 40 kWh EV that faced a delay would face the same delay per 100 km driven for the low power charging scenario. Increasing the charging power is seen to have a significant effect on the expected delay, with fewer than 0.1% of the journeys that faced a delay (shown in Figure 2.14 to be approximately 0.7% of total journeys) facing a delay of over 5 minutes for a 24 kWh EV. It is shown that in both charging scenarios, the delays faced by EVs with battery capacities of 60 kWh and above are very small: it is argued that as these represent such a tiny proportion of overall journeys taken, convenience parity for long journeys occurs for battery capacities of 60 kWh and above. For the sensitivity case, a higher proportion of journeys are delayed and those delays are more likely to be longer. The 45% of journeys in which a 24 kWh EV would face a delay of over 5 minutes per 100 km driven becomes 69% under the sensitivity case, and the 10% of journeys in which a 40 kWh EV would face a delay of over 5 minutes per 100 km becomes 20% under the sensitivity case.

2.3.3 Number of Infeasible Travel Diaries

Figure 2.16 shows the proportion of NTS travel diaries that are rendered infeasible by the presence of en route charging, i.e. when the time penalty attributed to en route charging in a given trip means that the arrival time would occur after the departure time of the subsequent trip.

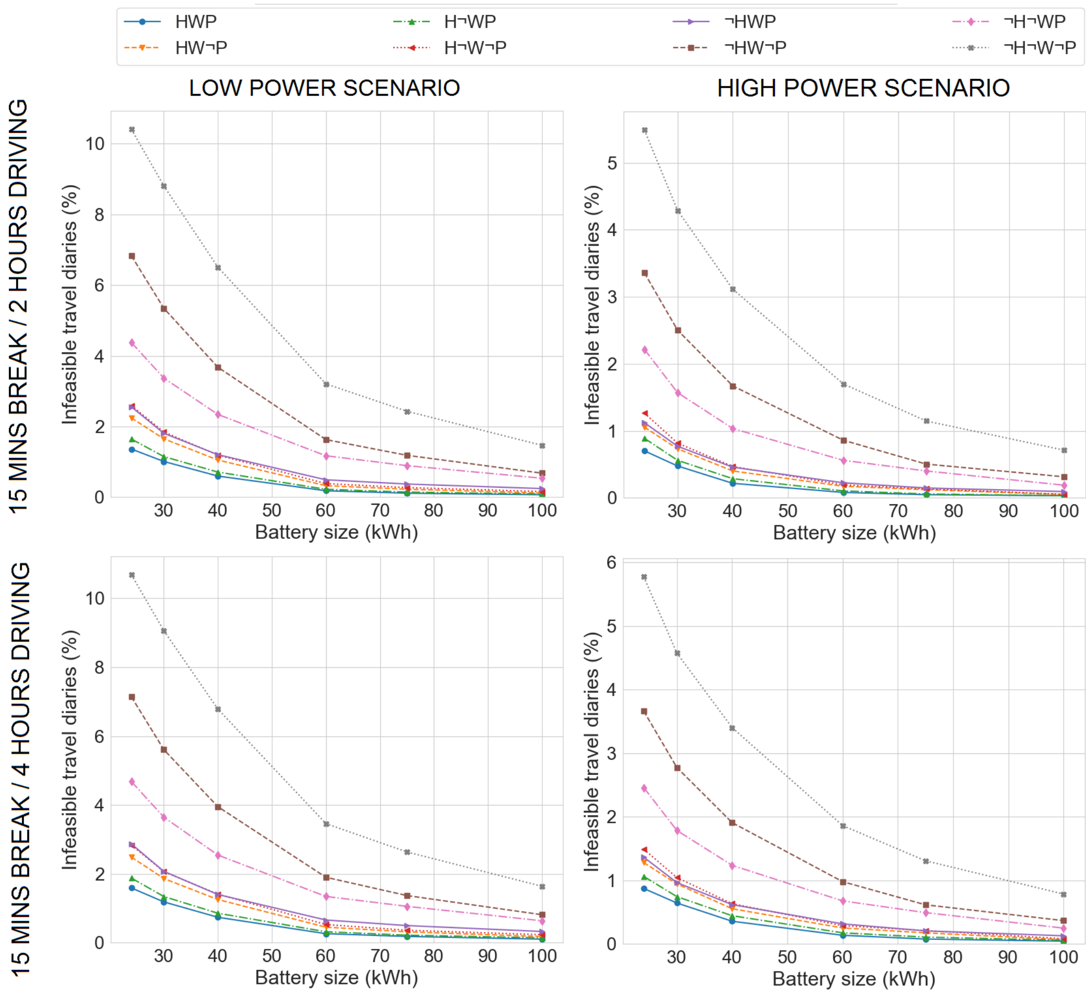

Figure 2.16: Proportion of UK National Travel Survey travel diaries made infeasible by EV charging for varying battery sizes and levels of charging access with comparison to ICV analysis for low power (left) and high power (right) charging scenarios for both the Highway Code Rule 91 case (top) and the sensitivity case (bottom)

Figure 2.16 shows another metric – besides the total time penalty – of the inconvenience of EV charging. For individuals who lack access to parked charging, a significant proportion (up to 10.7%, in the case of 24 kWh EVs under the low power charging scenario in the sensitivity case where drivers take a 15 minute break every 4 hours) of travel diaries are rendered infeasible by the use of an EV. Increasing access to charging is shown to dramatically reduce the proportion of travel diaries rendered unfeasible, with access to home charging or access to work and public charging reducing the proportion of infeasible travel diaries by up to a factor of 4. It is shown that increasing the charger power available also offers a significant improvement; the 10.7% of travel diaries for the above circumstances is reduced to 5.8% for the high power charging scenario. Increasing the battery capacity reduces the proportion of infeasible travel diaries, though for battery capacities of 60 kWh and over this rate of reduction decreases. It is suggested that this is due to a small proportion of travel diaries with longer journeys sufficiently close together such that an EV with any combination of the parameters trialled is unable to make the start time of the second journey from a delayed finish time of the first.

As shown in Figure 2.16, the assumption regarding how often breaks are taken during long journeys has a subtle effect on how many travel diaries are deemed infeasible. This could be due to the small presence of long trips in the data (Figure 2.13), or that the parking events tend to be of greater duration (and therefore more likely to be able to absorb any delay from having to stop and charge) for long journeys than shorter ones: the average parking duration following a journey of 2 hours or longer is 16.2 hours, compared to 10.6 hours for those following journeys under 2 hours (based on all journeys in the NTS dataset).

2.4 Discussion

Across all the results presented in Section 2.3, it is clear that achieving convenience parity between EV charging and ICV fuelling can be done by a combination of increasing battery size, increasing charging power and – most importantly – enabling access to charging at more locations.

It seems that the directions pursued by EV manufacturers (who will influence battery size and what level of power the vehicles can charge at) and business owners, employers and local authorities (who will influence the provision of publicly available charging locations) are moving toward a trend of increased EV charging convenience.

Battery sizes that have historically been constrained to the higher end of the market are becoming more widespread. For example, the Tesla Model S – a well-established long-range EV with battery configurations between 60 and 100 kWh – starts at £75,500 in the UK including government subsidies [92], remaining outside of the budgets of most would-be EV consumers. In 2019, Tesla are launching their own Model 3 in the UK with battery capacities between 50 and 75 kWh at the more modestly priced £38,800 after government subsidies [33] and Hyundai are pricing their Kona Electric with a 64 kWh battery at £32,845 after government subsidies [36]. Furthermore, 'affordable' EVs are increasing in battery size as new versions are released: as shown in Figure 2.3, three versions of the Nissan Leaf [53] have spanned three battery capacities in as many years from 24 kWh to 40 kWh.

Charging power is also increasing. 150 kW rapid charging is becoming the new norm for rapid charging, with BP Chargemaster – the UK's largest public EV charging network operator – planning to open 400 150 kW chargers by 2021 with the first being installed in 2019 [93]. The first 350 kW charger has been installed in the UK as of April 2019 [94], with cross-European joint venture Ionity planning to build 50 350 kW chargers in the UK by 2020 [95]. New EV models are moving towards being able to accept these levels of power: the Audi E-Tron can accept 150 kW [96] and the Porsche Taycan – to be released in 2019 – is confirmed to have a 350 kW charging capability [97].

It also seems likely that future EV users will have access to charging at more locations. As shown in Figures 2.9-2.12, having access to home charging renders convenience parity achievable at modest battery sizes and charging levels. For the estimated 43% of households that lack access to off-street parking in the UK [26], new options are emerging such as the Connected Kerb system, designed to allow low-impact charging infrastructure to be installed in the kerbs of residential streets [98] and the Char.gy network of lamppost charging [28], designed for those who park their vehicles on-street while at home. Increasingly, private companies are looking to provide free EV charging to attract more custom: as aforementioned, three of the UK's biggest supermarket chains have announced plans to install free-to-use EV charging infrastructure at their stores [75–77].

2.5 Chapter 2 Conclusions and Further Work

This chapter has presented analysis of 39,020 travel diaries from the UK National Travel Survey to investigate the inconvenience of EV charging relative to ICV fuelling. Inconvenience was quantified in terms of the time penalty suffered from charging or fuelling actions to service journeys taken over the course of a week.

The key contribution from is the quantitative analysis of the proportion of week-long travel diaries for which a driver could switch an ICV for an EV with no relative inconvenience related to maintaining a level of energy storage in their vehicles required to make the trips that they desire. It was found that the majority of EV drivers who have access to charging at home can expect convenience parity compared to ICV drivers, even for modest battery sizes. Increasing the battery capacity and charger power enables those without access to charging at home to experience a much lesser time penalty associated with charging than they would before, but there remains a big divide in the convenience of personal mobility between those who can charge at home and those who cannot. It is therefore established that a critical part of a future transportation system that supports EVs is an abundance of facilities with which people can charge as they park at home, regardless of whether that may be in a private driveway or not.

Aside from day-to-day driving as presented in the travel diary analysis, particular attention was given to journeys whose distance is greater than the range of the vehicle and hence cannot be made on a single charge. For this analysis, the assumption that drivers are compliant to the Highway Code had a significant effect. If they are compliant, it was found that, in the low power charging scenario for battery capacities of 40 kWh and above, the majority of trips which were of greater distance than the range of the vehicle would involve no delay resulting from charging that could not be fitted into breaks that should be taken anyway. This was true for all battery capacities modelled for the high power charging scenario. To the extent that the assumption of there being sufficient charging infrastructure such that a vehicle can immediately locate a charger upon reaching a minimum range of 25 km is valid, for battery capacities of 60 kWh and above, the proportion of journeys that are expected to face an additional delay from charging – 0.007% and 0.0002% for the low and high power charging scenarios respectively – are negligible. For the sensitivity case where drivers are not compliant with the Highway Code, a battery capacity of 60 kWh means that an expected 0.21% and 0.12% of trips are expected to involve a delay from charging from the low and high power charging scenarios respectively.

It has been discussed how the developing trends in the EV industry regarding battery size, charger power and charging infrastructure are likely to enable convenience parity for a wider section of EV users, and as such these trends are promising for the mass uptake of EVs that is widely cited as being required in order to reach *net zero* greenhouse gas emissions. Although the trends observed in the EV market may be moving in the right direction, there are still multiple challenges: EVs remain of high up-front cost and the development of extensive charging infrastructure – which on the basis of the results from this chapter could be argued as the most important technological development required for the mass uptake of EVs – requires significant capital expenditure, both in terms of the charging hardware itself and any grid reinforcements that must be made in order to accommodate the charging demand. Thus, continued support of the sector is critical.

Based on the contributions made by this chapter, the following pieces of further work are identified:

1. To disaggregate the travel data into sets that represent different driving behaviours, e.g. travel diaries that contain regular long journeys and those that are clearly that of a commuter. Results could then be published on the expected charging time penalty for different groups of drivers.

2. To expand upon the model of vehicle energy consumption by considering how the need to charge (and hence inconvenience associated with doing so) is affected by driving style and the additional power demand caused by air conditioning and heating.

3. To investigate alternative models of representing human behaviour and the impact of 'non-ideal' decision-making on the resulting inconvenience of charging.

4. To carry out analysis with the consideration of non-binary levels of access to charging. For example, while a driver might have access to charging at some public destinations (Table 2), they may not have access to charging at all public destinations they visit. Furthermore, if on-street home charging becomes widely

available, then any one charger may be expected to be available less than a private off-street home charger and the time penalty associated with finding a parking space with an available on-street charger would likely be greater. This rate of successful access to charging will have an impact on the results presented in this chapter, and the value of a sensitivity study into the extent of that impact is highlighted.

5. To investigate the relative cost and benefits of increasing battery size, increasing charger power and widening access to EV charging as methods of making EV charging more convenient.

6. To investigate how much EV charging will likely need to be done at various locations (within the workplace or public destination categories) based on the frequency at which vehicles visit these destinations. From this point, infrastructure planning could be informed as to the optimal number of charge points to install at each location and electricity network planning could be informed as to the likely demand profiles that would be seen at that point in the network.

7. To investigate the effect of continuing battery degradation on the results presented, given that the capacity of the battery will fade as they are charged and discharged, thus reducing the range of the vehicle and the charging rate attainable, thereby increasing the required frequency of charging stops and reducing the amount of energy that can be drawn from a given duration of charging.

8. To investigate the variation in willingness of EV drivers to undergo time penalties (and suffer inconvenience') as a result of charging based on variation in time of day and any activity that may be interrupted. This would allow more detailed analysis of likely driver charging behaviour, which would enable a more detailed impression of likely charging load on networks.

9. To investigate the impact of participation of bidirectional charging schemes, a.k.a. 'Vehicle 2 Grid' (V2G), on the resulting inconvenience of charging, given that participation in said schemes may reduce the ending SoC of charge events compared

to an approach such as this one, in which the final SoC is maximised.

10. To investigate the likely effect of charging pricing on the choices drivers make (with regards to which locations to charge at) and the resulting inconvenience of the new schedules.

Chapter 3

Characterising Electric Vehicle Charging Demand at Public Destinations and En Route Charging Forecourts using Smartphone Locational Data

3.1 Introduction

3.1.1 Motivation

As concluded in the preceding chapter, having the opportunity to charge while parked is vital in securing a level of convenience associated with EV use that would resemble the level of convenience of ICV use. While home-based charging was the most helpful type of parked charging to have access to, being able to charge at work and at public destinations such as supermarkets, shopping centres, gyms and cinemas — any destination where parking may be provided — was shown to be able to increase the level of convenience of EV charging. Furthermore, no matter how plentiful the supply of parked charging opportunities there is a subset of journeys, as shown in Figure 2.13, that outstrip the range of the vehicle driven and hence stops to charge en route must be taken.

As the EV sector continues to evolve, the provision of destination and en route charging infrastructure is expected to increase. [73] and [74] have suggested that EV drivers are likely to actively seek out destinations that offer charging opportunities, even at the expense of lengthening their own journeys. This explains the recent and ongoing growth in free-to-use public charging infrastructure, installed by business owners as a way of attracting additional custom. As of August 2019, three of the UK's biggest supermarket chains (Tesco, Morrisons and Lidl) have announced plans to install free-to-use EV charging infrastructure at their stores [75–77], highlighting a recognition by businesses who provide parking of the draw that can be offered by EV charging facilities. Meanwhile, Shell and BP – two of the largest fuel suppliers in the UK – are installing 150 kW rapid charging stations on their petrol station forecourts [93, 99]. Due to the generally higher charger power ratings at destination and en route charging facilities compared to at-home charging, network operators [100] and policymakers [101] have expressed concern about the effect of this type of EV charging on the electricity system.

As discussed in Section 1.3, the demand of destination and of en route charging on the electricity system are expected to be different to that of domestic charging – firstly due to differing arrival times and lengths of stay, and secondly due to differing charger power ratings.

3.1.2 Contribution

The key contribution of this chapter is to provide a set of modelling techniques to characterise the likely temporal variation in EV charging demand at both public destinations, for which cars are parked for durations ranging from 10 minutes to 3+ hours, and en route EV charging 'forecourts', for which drivers pause their journeys for the sole purpose of charging their vehicles. These characterisations are derived from analysis of smartphone locational data from the Popular Times feature in Google Maps.

Section 3.2 presents an in-depth review of the literature surrounding the characterisation of EV charging at public places, with an emphasis on works which have sought to utilise some form of mobility data. The relative merits of different methods are discussed, and gaps in the literature are identified in which the work presented in this chapter sits. Section 3.3 presents a description of the data source used in this chapter – data from the Popular Times feature in the Google Maps website/smartphone application – and discusses its application to this work, its advantages over other forms of mobility data available and any limitations. Section 3.4 presents a method for the characterisation of rapid en route charging demand at an 'EV forecourt', a charging location analogous to a petrol station, using data from the Google Maps Popular Times feature. Results are presented in terms of the probability that the demand from an EV charging forecourt will exceed a certain value in a certain time period, and the results are combined with loading data of a real distribution system in Scotland. Section 3.5 presents a method for the characterisation of destination charging at amenities such as supermarkets, shopping centres, gyms and cinemas, again using data from the Google Maps Popular Times feature. The method and assumptions associated with destination charging are different to those concerning en route charging. The method is demonstrated by probabilistic characterisations of charging demand in gym car parks and via a specific case study of a hypothetical transmission-connected charging facility at a large GB shopping centre. The findings of this chapter are summarised in Section 3.6.

3.2 Literature Review

There are many works in the literature concerned with the optimal placement of public EV charging stations, based on combinations of the best options to EV drivers, the road network and the power system. In [102], the authors present an equilibrium modelling approach to combine a road network with that of an electrical system and placement of a series of charging stations, establishing a cost minimisation of individual EVs between seeking the lowest cost charging option and the shortest distance travel option to derive usage profiles of the charging stations. The authors in [103] present a model based on origin-destination analysis of a fleet of vehicles (assuming that every vehicle has an origin and a destination, and will travel between the two in the shortest route possible constrained by the geometry of the road network) and uses it to optimise the location of fast charging infrastructure on a German autobahn. Whereas the previous two works [102,103] are only concerned with the maximisation of the provision of service to EV drivers, [104] presents a combination of the needs of EV drivers with that of the power system by means of a multi-objective optimisation of the maximisation service provision to EVs and the minimisation of power losses and voltage deviation. In [105], the authors present a multi-objective optimisation method of returning the optimum location and power rating of en route charging stations so as to minimise initial investment and maximise traffic flow through the charging stations (and hence revenue); thus maximising the return from investment. [106] presents a method that combines the transport and electrical distribution networks into a single network and minimises a cost function comprising of the costs to operate the EV charging stations and the costs associated with electrical losses to establish the optimum number of and location of charging stations. [107] presents a work with no consideration of the power network, but presents origin-destination analysis on an extensive traffic dataset and uses an optimisation approach to minimise the total cost of a set of charging stations, such that the number of en route EV charging stations is minimised to cater for that population of traffic. All the above works use either a multi-objective optimisation approach to derive the optimal location of a set of charging stations given the constraints of a road network and/or a power network. Though [108] presents a fuzzy TOPSIS method (Technique for Order of Preference by Similarity to Ideal Solution) that can be used to pick the most favourable solution from a set of solutions that are deemed feasible, it is suggested that there is in reality very little opportunity for 'greenfield' EV charging infrastructure, and that the development of charging infrastructure will not necessarily be influenced by what the optimal location of them would be, but rather the locations of already existing businesses where charging infrastructure could be developed (e.g. supermarkets, shopping centres etc.) and motorway service stations, which are already constrained to the locations at which they exist. The work presented in this chapter seeks to quantify the likely demand at hypothetical EV charging infrastructure developments based on the activity profiles of the businesses at which it is likely to exist.

Works that attempt to model the charging demand at public charging stations are comparatively few, due to the longstanding emphasis on EV users charging their vehicles at home. In [84], authors present analysis of the temporal variation of EVs passing through a fast charging station based on the frequency and duration at which conventional vehicles are visiting petrol stations, which is analogous to how data are collected for charging destinations in this study. However, as the data are manually collected, the sample size is small (four petrol stations). The authors in [109] use traffic flow data to drive an EV charging demand model at various charging stops, which although uses real data as in this chapter, a dependency is assumed between traffic (vehicles being on the roads) and their seeking to stop and charge. It is suggested that in reality, the likelihood of individual drivers stopping to charge is related to their remaining range and the time of day (and hence the EV charging activity in relation to other planned activities in the day). In [110], a model is presented which analyses the likely demand for en route EV charging stations based on a large dataset of over a million mobile phone call records over a four-month period. While the approach of using a large-scale mobile phone-based dataset is similar to that proposed in this chapter, it is suggested that call records are of limited value when analysing individuals' mobility: aside from it generally being against the law to use a mobile phone while driving, use of mobile phones for calling is in significant decline in favour of internet-based communication apps such as WhatsApp and Facebook (whose usage would not be recorded in call records), with a quarter of UK smartphone users reportedly using their phones to make calls less than once per week [111]. It is proposed that the method presented in this chapter can be used to grow the body of knowledge in the topic of EV charging demand characterisation. The method of using large-scale smartphone locational data from such a ubiquitous source as Google Maps – though not without its limitations as discussed in Section 3.3 — to inform the models represents a shift towards utilising big data in the effective planning of transport and energy systems.

3.3 Smartphone Locational Data from the Google Maps Popular Times Feature

3.3.1 Data

The Popular Times feature [112] within the Google Maps website and smartphone application allows users to see when a certain business is likely to be crowded, based on anonymised positional data collected from smartphone users with the Google Maps application installed and location history enabled over the last several weeks. The display shows an average popularity for each hour of each day of the week, as a percentage value of the peak popularity. An example is shown in Figure 3.1 for a particular large gym in the West of Scotland.

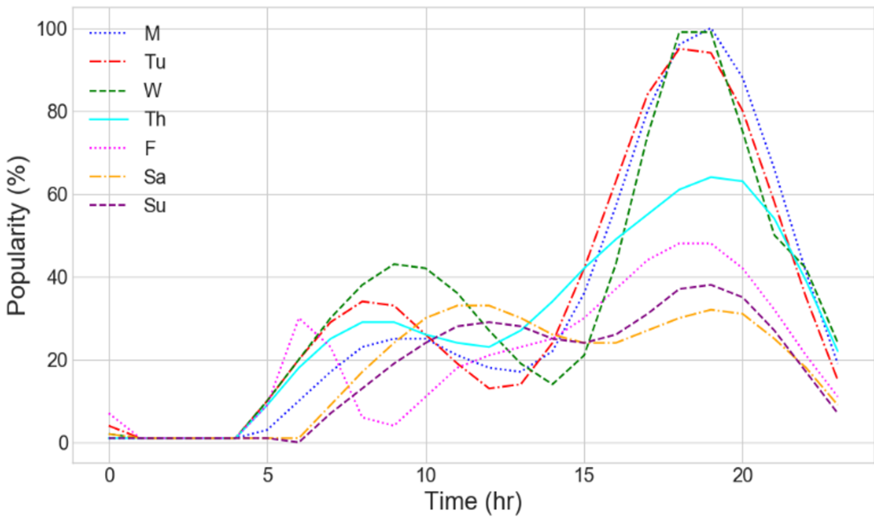

Figure 3.1: Example of Google Maps Popular Times data for a particular large gym in the West of Scotland

3.3.2 Limitations

Firstly, the data is captured from visitors to these amenities only if they are smartphone users with the Google Maps application installed and have not actively disabled location services[1]. While this method is likely to capture a great many users (37 million people –

[1] While it is possible to disable location services within the app's settings, it has a negative impact on the app's convenience as it no longer remembers users' own locations (e.g. home, work) and therefore

81% of UK adults – were smartphone users in 2016 [113] and Google Maps was installed on 57% of US smartphones in 2017 [114]), this could introduce a selection bias in the results if those who are less likely to be captured in the data are more likely to visit these amenities at certain times.

Secondly, the popularity data is presented as an averaged percentage of the peak and there is no indication of the absolute number of visitors. The work presented in this chapter assumes that amenities are well-suited to their local markets and, although it is expected that not all users of these amenities will travel there by car, '100% busy' in the Google data is taken to correspond to a 100% full EV charging car park. If using this method to examine amenities in a particular location, such as in Section 3.5.6, more detailed work to ascertain the peak popularity should be carried out.

Thirdly, as the data is compiled and presented for seven days of the week, no seasonal variation can be derived.

Fourthly, the data represents all people within the business' footprint – including passengers of the cars arriving, any employees and perhaps most notably people who have arrived without the use of a car. Therefore, it is stated that a significant assumption made in this work is that the rate of occupancy of a business by cars is directly proportional to the rate of occupancy of a business by total individuals.

Despite these limitations, it is suggested that using smartphone locational data for activity holds distinct advantages over using survey-based data. Firstly, the data encapsulates individuals' actual movement patterns rather than what they recall or divulge. Secondly, the burdensome nature of surveys results in a relatively low sample size: while the NTS data used extensively in this thesis covers around 15,000 residents per year, the approach used in this chapter has the potential to provide recent mobility data on tens of millions of UK vehicle users.

makes it less straightforward to plan journeys. It is not known how many individuals choose to disable their location settings.

3.4 Rapid En Route Charging Model

3.4.1 EV Forecourt Concept

The objective of this work was to develop a probabilistic method for the characterisation of the demand resulting from EV fast charging forecourts based on the activity of current UK petrol stations derived from smartphone users' anonymised positional data available from the Google Maps Popular Times feature. The assumption that the activity of EV charging forecourts will follow the activity of petrol stations is based on the idea that the two activities are analogous: drivers will visit the site only to replenish the energy content storage of their vehicles, they will wait in a queue if the forecourt is full until a space becomes available. The EV forecourt concept is depicted in Figure 3.2.

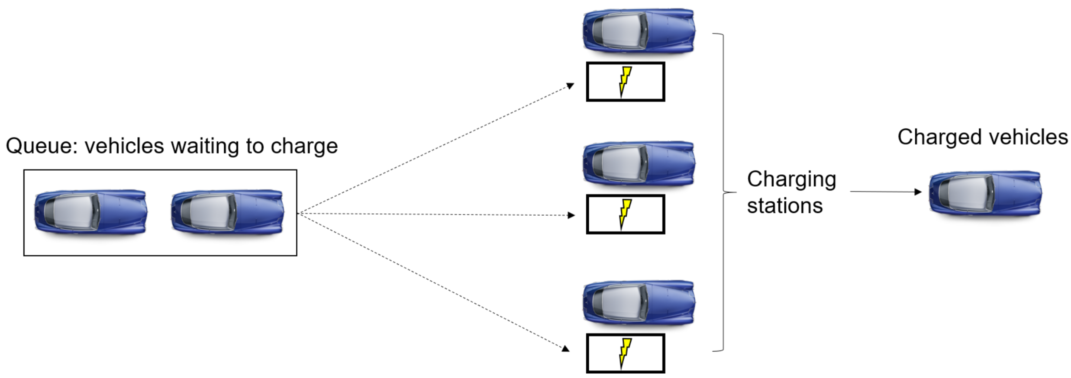

Figure 3.2: EV charging forecourt concept

The number of charging stations in the forecourt shown in Figure 3.2 can be any positive integer. In the remainder of this section, it is set to 8 charging stations in common with [115]. This also reflects the average number of pumps at a UK petrol station, which was reported in 2013 to be 7.5 [116].

3.4.2 Arrival Profile of EVs

Popular Times data was retrieved for a sample of 2,256 existing petrol stations in Great Britain in areas surrounding major cities (Scottish Central Belt, Glamorgan, Yorkshire, Greater London, Greater Manchester, West Midlands, Avon, Merseyside and Tyneside). Of the 2,256, 476 are supermarket-owned, 1,694 are independent/oil company-owned and 86 are at motorway service stations. For comparison, there were 8,442 petrol stations in the UK in 2018 [72]: the sample used in this work makes up just over a quarter of the population.

Figure 3.3 shows a density plot of all Popular Times data for all 2,256 petrol stations in the sample. The lighter colouring shows a higher incidence of data points. Given the significantly lighter colouring throughout the profile on Friday, it is shown that petrol station activity on a Friday is generally easier to predict than on a Saturday. The peak on Fridays is shown to be most commonly around 15:00-16:00, whereas on a Saturday this is much earlier at around 12:00-13:00.

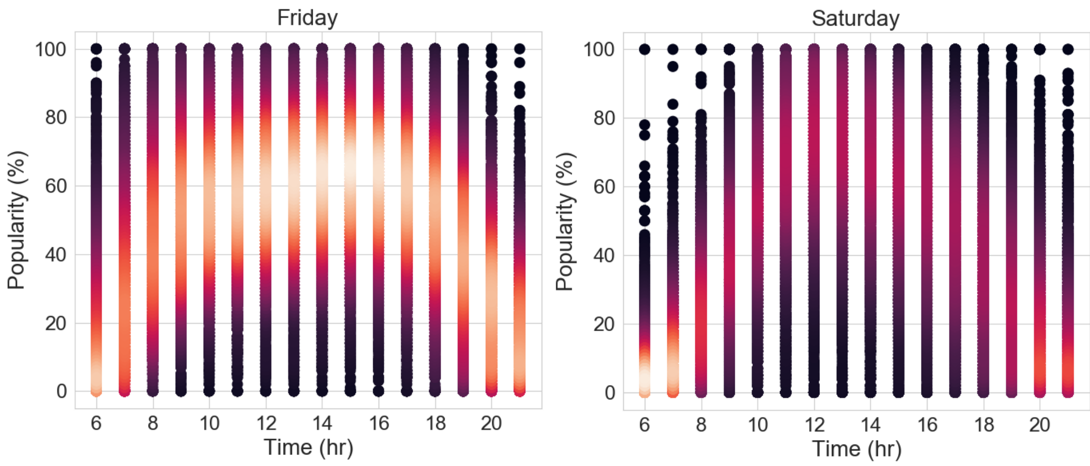

Figure 3.3: Density plots of Google Maps Popular Times data for 2,256 petrol stations in GB – Friday (left) and Saturday (right)

Figure 3.4 shows CDFs for the popularity (%) according to the Popular Times data for each hour of the day for Friday and Saturday.

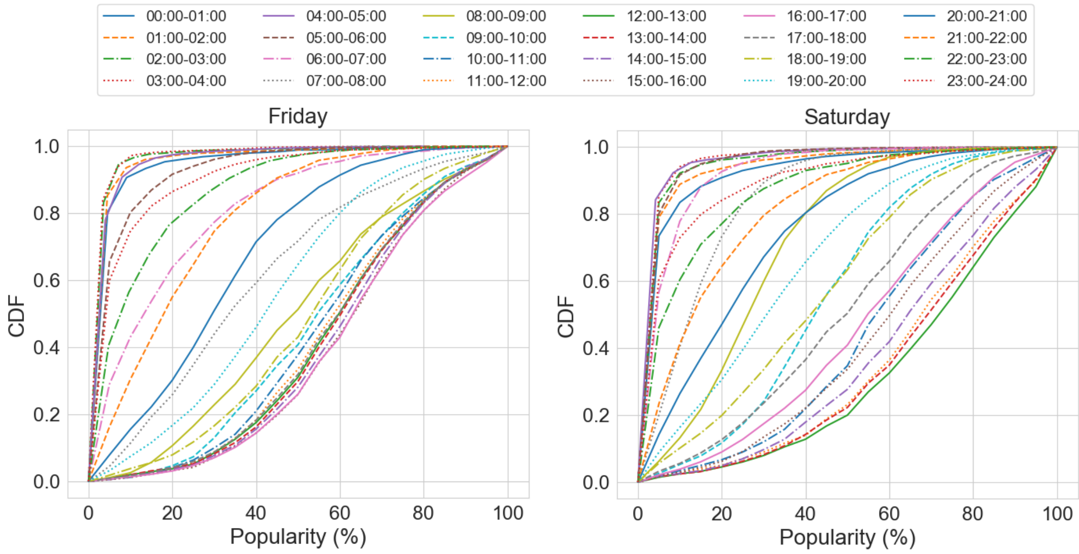

Figure 3.4: Cumulative distribution functions for popularity at petrol stations in varying hours of the day – Friday (left) and Saturday (right)

In order to generate an arrivals profile of EVs at the forecourt, the forecourt activity was represented by a multiple server, single queue problem with a Poisson arrival process and deterministic service time (denoted as $M/D/s$ as per Kendall's notation in [117]).

Little's theorem (3.1) [117] is used to derive a distribution of the arrival rate μ (with average arrival rate $\bar{\mu}$) in terms of the average number of agents in the system N (i.e. the forecourt occupancy) and an average service time T (i.e. the total time spent at the petrol station) (3.2).

$$N = \mu T \tag{3.1}$$

$$P(\mu) = e^{(-\frac{N}{T})} \frac{(\frac{N}{T})^{\bar{\mu}}}{\bar{\mu}!} \tag{3.2}$$

Recall that the total time spent in a petrol station was found for a sample of vehicles in Section 2.2.9. The median total time was found to be 251 seconds, or 4.2 minutes. The average service time T in (3.1) is set accordingly.

Based on 8 fuelling stations in a petrol station, the arrival profile of vehicles in such a forecourt can be generated. An example of this is shown in Figure 3.5.

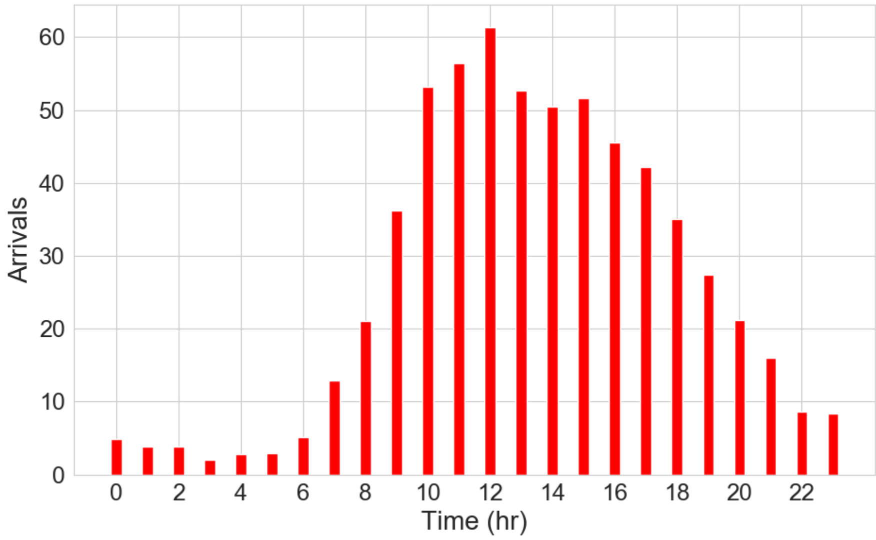

Figure 3.5: Example arrivals profile (vehicles/hour) for petrol station with popularity sampled from Google Maps Popular Times data

3.4.3 Forecourt Parameters

As already mentioned, the number of charging stations in the forecourt simulated in this study is 8. The other key parameter for the forecourt is the power rating of the chargers. The power rating of fast EV charging infrastructure is a trade-off between convenience to the user, limitation of battery stress and cost to the infrastructure developer versus the local demand for using them. If charging rates are too low, users would face perhaps an unacceptable amount of inconvenience as they wait for their vehicles to charge. If they are too high, users may be deterred from using them at their rated capacity out of concern for reductions in battery life; capital costs for their acquisition and connection will also increase with charger rating. In the literature, fast charging rates are in the range 100-350 kW [109, 115, 118]. The rating for this work was chosen to reflect a reasonable queue size (explained in more detail in Section 3.4.5), which was set such that the average maximum daily queue time of an 8 charging station forecourt over 10,000 trials[2] based on Saturday data (the busiest day for UK petrol stations) would not exceed 2 minutes, in accordance with what would be considered reasonable at a

[2]This number of trials was selected to minimise the error in the reported results, at the limit of what was deemed a reasonable amount of computational burden. It is suggested that this number of trials is sufficient, as it exceeds the number of data points (2,256 petrol stations).

current UK petrol station. For the ‘all EVs’ case (Figure 3.6), 100 kW gave an average maximum queue length of 2.0 minutes. For the ‘BEVs only’ case, 200 kW gave an average maximum queue length of 1.9 minutes. The average time spent charging for both cases was less than 5 minutes.

3.4.4 Vehicle Parameters

Battery Capacity

A histogram showing the probability distribution of EV battery capacities (kWh) for UK sales in 2017 [119] is presented in Figure 3.6, from which the simulated vehicle’s battery size was randomly sampled. Two series are shown; one being for all EVs (including Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs)) and one for BEVs only. It is perhaps reasonable to suppose that, as PHEVs have an internal combustion engine to rely on, BEV users (who normally have larger batteries to charge) would be more likely to charge at EV forecourts.

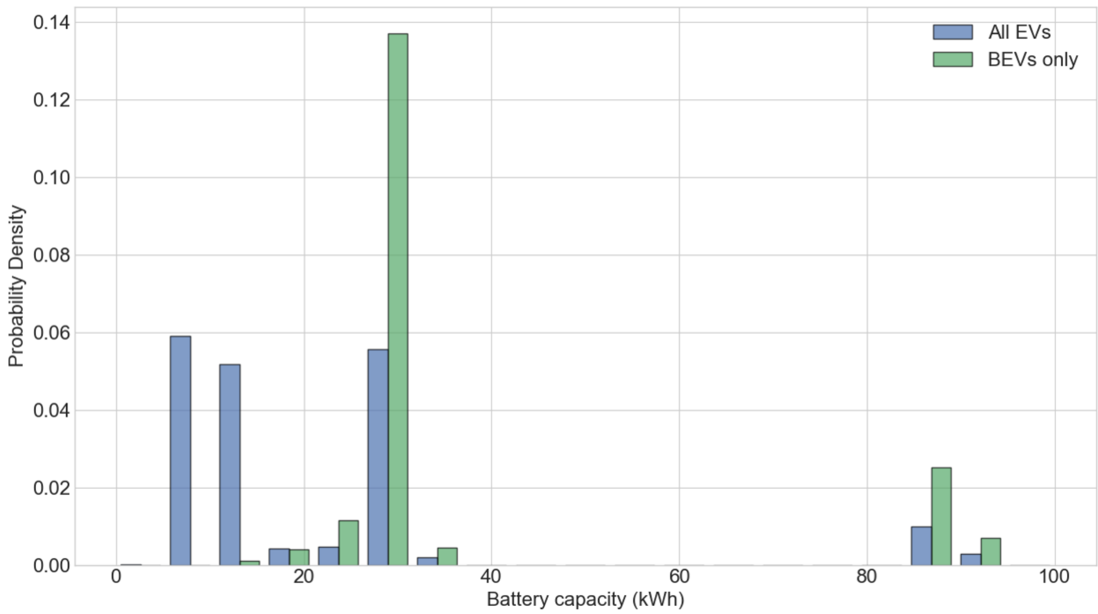

Figure 3.6: Histogram showing distribution of battery sizes for UK EV Sales in 2017, source: RAC Foundation

If the ‘BEVs only’ option is selected then the energy requirement of vehicles increases due to their larger battery capacities. For a given charger capacity and number of charging stations, this has the effect of lengthening the queue as previously discussed. However, by increasing the charger power the queue can be kept to a similar length and the overall demand profile will tend towards a scaled version of that for the 'all EVs' case. Therefore, only results from the all EVs case are presented in this chapter as an example of the method.

State of Charge on Arrival and Added Charge as a Proportion of Empty Capacity

The SoC of a battery upon starting and finishing EV charging is often modelled by Gaussian distributions as exemplified by Qian et al [120]. However, Yi and Li [121] present χ^2 test results to argue that a Beta distribution offers a better goodness of fit to real charging behaviour than a Gaussian distribution does. According to Marra et al. [83], a Li-ion EV battery should ideally be cycled between 20% and 90% SoC; this was used to inform the setting of Beta distribution parameters α and β. SoC on arrival was treated as an independent variable with $\alpha = 2$ and $\beta = 5$, shown by the blue line in Figure 3.7. This gives a modal SoC on arrival of 20% and a mean of 29%. The post-charging SoC was derived by sampling a Beta distribution describing the added charge as a proportion of empty capacity, to ensure the EV cannot charge to above 100% or below its SoC on arrival. Parameters for the added charge Beta distribution were tuned by taking one million samples from the SoC on arrival distribution (blue line) and the added charge distribution (green line) for various α and β to produce a histogram of post-charging SoC. The probability of an EV leaving the forecourt with an SoC above 90% is less than 5%, which reflects the ideal charging behaviour in [83] but allows some users to violate it. The added charge Beta parameters were set as $\alpha = 3.2$, $\beta = 2.6$.

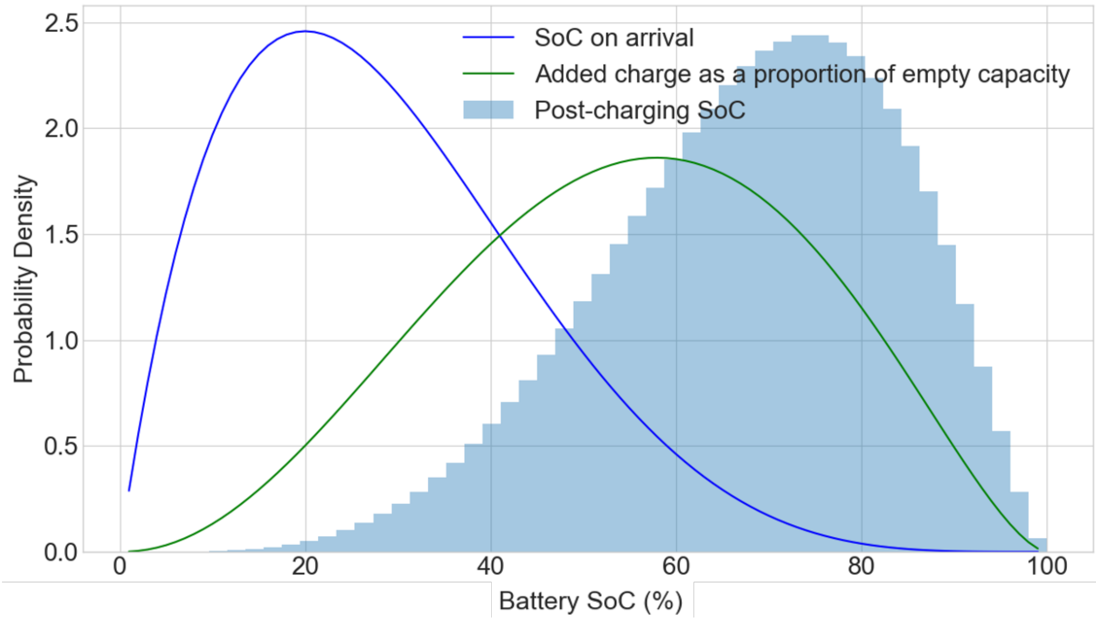

Figure 3.7: Beta distributions for vehicle state of charge on arrival and added charge as a proportion of empty capacity

Arrival Time

Within the hour, the vehicle's arrival minute was randomly assigned as a random integer between 0 and 59.

3.4.5 Queuing Model

Conversely to the public destination charging model in Section 3.5, vehicles will only stay at the forecourt for as long as it takes them to charge. The time it takes them to do that – resulting in their departure time t^d – can be derived by consideration of the CC-CV battery charging profile originally presented in Figure 2.6. Given the SoC on arrival S_e^s and SoC on departure S_e^d of charging event e sampled from the distributions in Figure 3.7, it follows from equation (2.6) that the energy gained ΔE_e by the vehicle for a given charging event e between the arrival time t_e^s and departure time t_e^d is (3.3).

$$\Delta E_e = \begin{cases} P_e^{DC}(t_e^d - t_e^s), & S_e^s \leq \gamma, S_e^d \leq \gamma \\ \int_{t_e^\gamma}^{t_e^d} P_e^{DC} e^{-\lambda_e(t-t_e^\gamma)} dt + P_e^{DC}(t_e^\gamma - t_e^s), & S_e^s \leq \gamma, S_e^d > \gamma \\ \int_{t_e^s}^{t_e^d} P_e^{DC} e^{-\lambda_e(t-t_e^\gamma)} dt, & S_e^s > \gamma, S_e^d > \gamma \end{cases} \tag{3.3}$$

where all symbols have the same meaning as they did in equation (2.6). Rearranging (3.3) in terms of t_e^d gives (3.4).

$$t_e^d = \begin{cases} t_e^s + \frac{\Delta E_e}{P_e^{DC}}, & S_e^s \leq \gamma, S_e^d \leq \gamma \\ t_e^\gamma - \frac{\ln \Lambda_e}{\lambda_e}, & S_e^s \leq \gamma, S_e^d > \gamma \\ t_e^\gamma - \frac{\ln \Omega_e}{\lambda_e}, & S_e^s > \gamma, S_e^d > \gamma \end{cases} \tag{3.4}$$

where Λ_e and Ω_e are given in (3.5) and (3.6) respectively.

$$\Lambda_e = 1 + \lambda_e(t_e^\gamma - t_e^s) - \frac{\lambda_e}{P_e^{DC}} \Delta E_e \tag{3.5}$$

$$\Omega_e = e^{\lambda_e(t_e^\gamma - t_e^s)} - \frac{\lambda_e}{P_e^{DC}} \Delta E_e \tag{3.6}$$

ΔE can be equated to the capacity of the battery in charge event e C_e multiplied by the difference between the post-charge SoC S_e^d and the SoC on arrival S_e^s (3.7).

$$\Delta E_e = C_e(S_e^d - S_e^s) \tag{3.7}$$

The demand drawn by the forecourt at any given minute is equal to the total charging power, summed across all the cars plugged in. The power that a given car is charging at is found as in equation (2.6). To simulate busy periods at the forecourt, a queuing model was developed. Each time a car arrives it is assumed to begin charging immediately and leave when its charging time is finished, unless the number of vehicles connected is equal to the number of charging stations (i.e. the forecourt is full). In this case, the car must join a queue. The queue will continue to grow as more cars arrive and join the back of the queue. Cars will wait in the queue until the next vehicle leaves the forecourt, at which point the vehicle at the front of the queue connects to the free charger and their leave time is adjusted accordingly (their charge duration is assumed to be the same). It is assumed that vehicles join one queue for the forecourt and they take charging stations on a first come, first served basis. Once a vehicle joins the queue, it is committed to waiting to be charged and the queue length has no limit.

3.4.6 Results

Monte Carlo Simulations of EV Forecourt Demand Profile

The 8x100 kW EV forecourt simulation described was run for 10,000 trials. A probability distribution of the demand time series produced is shown by a 3D histogram in Figure 3.8. For a given time of day, the probability that a simulated EV forecourt will draw a particular power demand is given by the bar height.

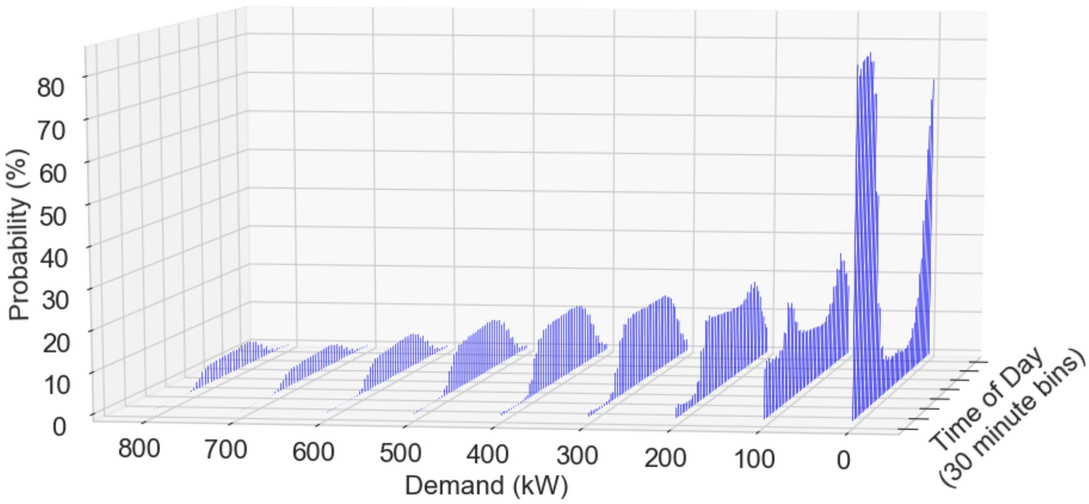

Figure 3.8: 3D histogram showing probability distribution of 10,000 trials of an 8 x 100 kW forecourt simulation based on Friday popularity data

Figure 3.8 shows that there is significant variation of the forecourt's demand levels for most of the day. The discrete nature of the distribution is due to the constant-charging assumption used; as the distribution reflects forecourt occupancy, the total demand of the forecourt can only take one of nine levels between 0 and 800 kW. It is shown that probability reduces with increasing power, but there remains a 5-10%

likelihood of peak demand in the mid-afternoon.

Statistical Comparison with Existing Network Load

To assess the impact of an EV rapid charging forecourt on an existing electricity system, system planners would need to know the combined loading of the existing load and that presented by the EV charging station. Traditionally, the maximum demand would be equal to the present maximum network loading plus the maximum demand drawn by the EV forecourt. However, probabilistic methods can be used to better assess the impact of new load based on their temporal variation. For example, if the EV charging load and present network loading were to peak at different times, or if the combined loading breaches network limits for only a small proportion of the time, then network reinforcement could potentially be deferred in favour of employing a number of 'smart' grid technologies.

An EV charging forecourt at a rating of 800 kW would likely be connected to a primary distribution feeder (6-11 kV), either directly or via a dedicated secondary transformer, rather than at a lower voltage as is the case for residential charging as discussed in Chapter 4. To compare the EV forecourt demand characterisation with that of a network on which it would typically be connected, secondary (11/0.4 kV) substation loading data from SP Energy Networks' *Flexible Networks* project [122] were used to construct a CDF (Figure 3.9) of the combined loading of 10,000 MC trials of an 8x100 kW EV forecourt based on Tuesday Popular Times data with all monitored winter weekdays in the period 2013-2015 for all secondary substations on an 11 kV feeder covering suburban areas and major roads in St Andrews, a town on Scotland's East Coast.

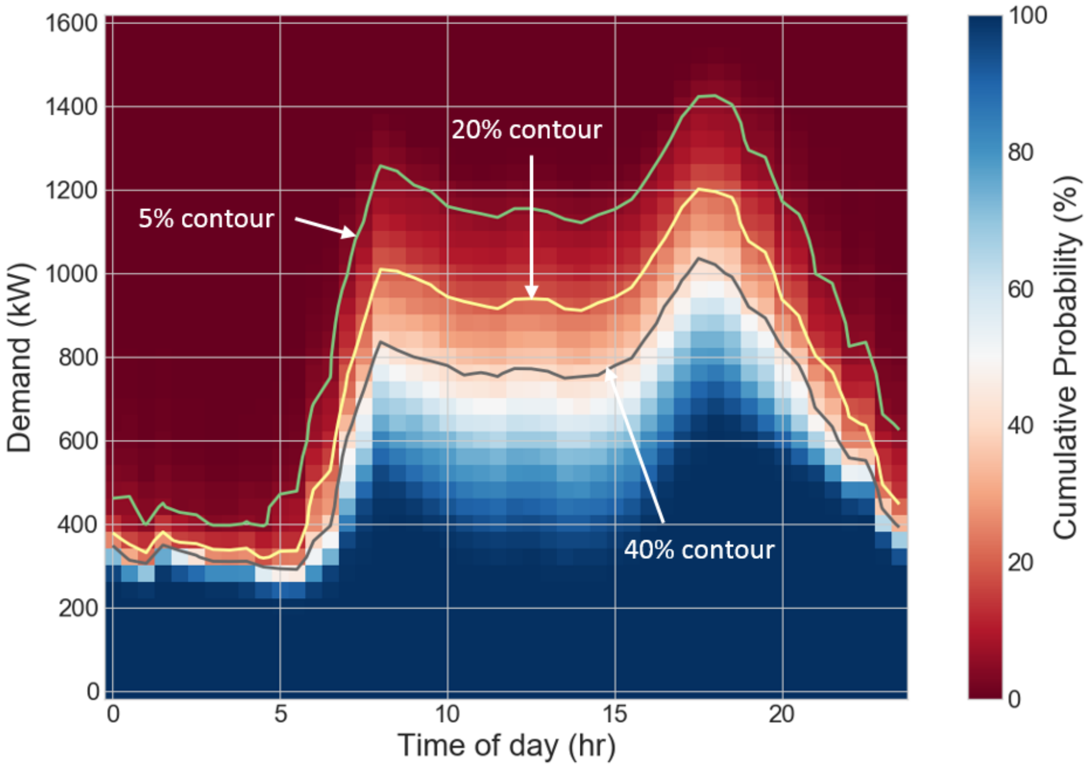

Figure 3.9: Cumulative distribution function of combined loading of 8 x 100 kW EV forecourt simulation (Tuesday) and St Andrews Feeder 24, winter weekdays 2013-2015

The method demonstrated in Figure 3.9 provides an estimate of the likelihood that the feeder peak, following the integration of an EV forecourt, will exceed a certain value on a given day. For example, it is shown that there is a 5% probability that the peak on a given Tuesday will exceed approximately 1420 kW – 175% of the original peak loading – at around 17:30. The method also allows quantification of the amount of time the feeder loading will likely be above a determined value. This temporal aspect would be valuable in assessing the suitability of smart grid technologies, which often exploit the inherent diversity and temporal variation in electricity demand. For example, real-time ratings of assets could allow the system to exceed thermal ratings for a short time. Alternatively, a flexible connection could be given to the EV forecourt to enable its peak to be reduced in times of network peak and dynamic pricing could be used to encourage vehicle users to charge outside of times of network peak (e.g. in the morning) or at times of high local generation output. Furthermore, on-site battery storage could be employed at the EV forecourt to smooth out peaks in its demand.

3.4.7 Discussion

This section has presented a characterisation of electrical demand profiles of EV fast charging forecourts, which are likely to be commonplace in high EV-uptake scenarios. The characterisation is based on current petrol station usage data derived from smartphone locational data collected by Google's Popular Times feature.

The fundamental assumption on which this work is based, that EV charging is likely to be done in the same way as fuelling of petrol and diesel-powered cars, can of course be called into question. However, in a future scenario where rapid charging is preferred as a main charging method to residential charging, such as for the set of EV drivers who lack access to parked charging as described in Section 2.3, the two activities are essentially analogous. As discussed in Section 1.3, a high EV-uptake future is likely to include a mix of en route charging, destination charging, workplace charging and residential charging. The method presented in this section can be used to evaluate how the rapid charging portion contributes to the total EV charging load. Following this assumption, there is likely to be significant variation in the demand of rapid EV charging forecourts. The method presented in this section could be used across an entire distribution network to model uptake of various modes of EV charging and how the temporal variations in their demand interact with one another. This could be used to assess the requirement for network reinforcement and evaluate the feasibility of 'smart' alternatives in preparing distribution networks for the widespread electrification of transport at minimum possible cost.

To improve the accuracy of the results, analysis of the petrol stations included in the data is recommended. It was suggested that vehicle fuelling activity is related to local employment patterns and proximity to key infrastructure; disaggregation on these factors and others would allow analysis on the basis of a number of more focused type-specific characterisations.

Aside from rapid-charging forecourts, a similar method using Google Maps Popular Times data could be used to characterise destination charging at locations such as gyms, supermarkets, cinemas and shopping centres. The main difference is that while vehicles are assumed to travel to en route charging stations only to charge their vehicles and only stay for the length of time it takes them to do that, vehicles will stay at destination charging stations for as long as they are going to be at the destination. This analysis is presented in Section 3.5.

3.5 Public Destination Charging Model

3.5.1 Overview

A similar method to that presented in Section 3.4 is presented in this section for the characterisation of destination charging: charging while the driver is parked for periods ranging 10 minutes to 3+ hours at amenities such as supermarkets, shopping centres, gyms and cinemas.

The key difference between the two types of charging, as previously discussed in Section 1.3, is that whereas drivers will only stay at an en route charging station as long as it takes to gain the amount of energy desired, drivers will stay at a destination charging facility for as long as they would have done anyway, regardless of how they came to be there and the amount of energy they receive is a function of their duration of stay and the power rating of the charger.

3.5.2 Electric Vehicle Fleet Charging

Charging Philosophy

Controlled EV fleet charging can be used to minimise stress to the network [123], match times of high charging demand to times of low energy cost [124] or high renewable output [125, 126], or maximise service provision to the EV user [82, 127].

Proposals for controlled EV fleet charging presented in [82, 123–126] all rely on bidirectional flow to and from the vehicle – V2G – and some extent of consumer engagement over and above parking and plugging in, ranging from the EV user entering their intended stay time [125] to having the EV user enter four separate 'preference parameters' upon parking [82]. Although the approaches in these studies can lead to optimised charging schemes in an ideal world, in providing user engagement the system is inherently vulnerable to unpredictable non-ideal behaviour likely to compromise the economic benefits of smart charging [128]. For example, users could 'game' the system by entering a false intended stay time in [125] to prioritise the charging of their EV over others. The option to allow V2G operation would have to be consented by the vehicle owner, yet the chances of this happening may be reduced by findings that doing so has a detrimental effect on battery longevity: according to [78], a 'base case' EV following the median trip distances from the NTS could face a 57-fold increase in daily battery degradation rate from providing ancillary services and a 115-fold increase from providing bulk energy services by operating in V2G mode.

For these reasons, this work proposes a simpler EV fleet charging algorithm with unidirectional operation that seeks to provide optimal service provision to all users with no consumer engagement over plugging the car in to the charger, given the available grid capacity.

EV Charging Car Park

The work presented in this section is based on the concept of a multi-terminal DC charging network with one central AC/DC converter and a separate DC/DC converter at each car parking space. The concept is well established; presented in more detail in [126, 129] and replicated in Figure 3.10.

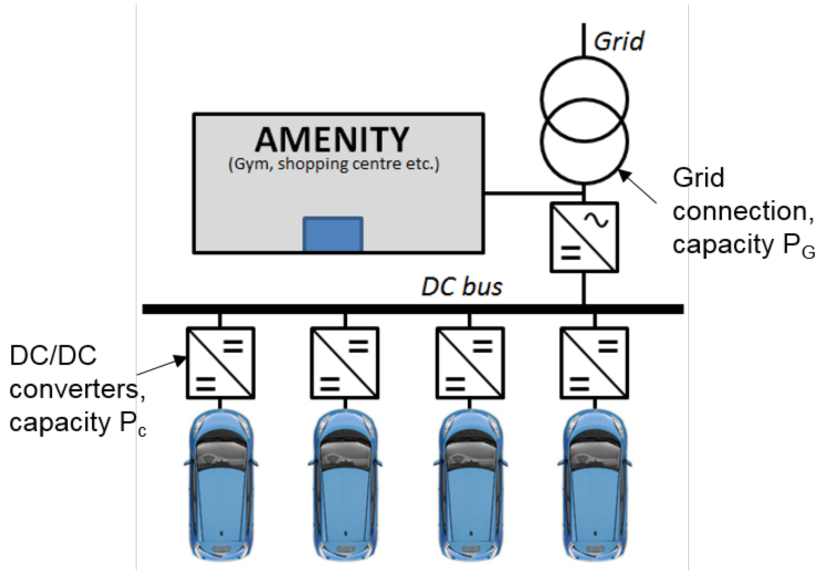

Figure 3.10: Proposed topology for EV destination charging car park

3.5.3 EV Parameters

SoC at Start of Charging Event

As in Section 3.4, the SoC upon arrival is modelled with a Beta distribution. However, unlike the en route charging model, in this model there is no pre-defined target SoC that the vehicle wishes to charge to: they will receive the amount of energy as determined by their duration of stay and the power rating of the charger. For this model, the Beta shape parameters α and β are derived using a 'method of moments' estimation. The shape parameters are derived from data of the SoC at the start of charging for 2,494 charging events at 'public' locations monitored as part of the *SwitchEV* electric vehicle trial [130], which ran from March 2011 to May 2013 in Northeast England to provide insight on how individuals use and charge EVs, with an emphasis on workplace and public charging. Analysis of the *SwitchEV* data and a full description of how the Method of Moments is used to derive the Beta shape parameters is given in the Appendix of this thesis. Based on this data, the Beta distribution parameters are set at $\alpha = 2.27$, $\beta = 2.18$ which derives a mean SoC on plugin of 51%. The probability density function (PDF) of this Beta distribution is shown in Figure 3.11.

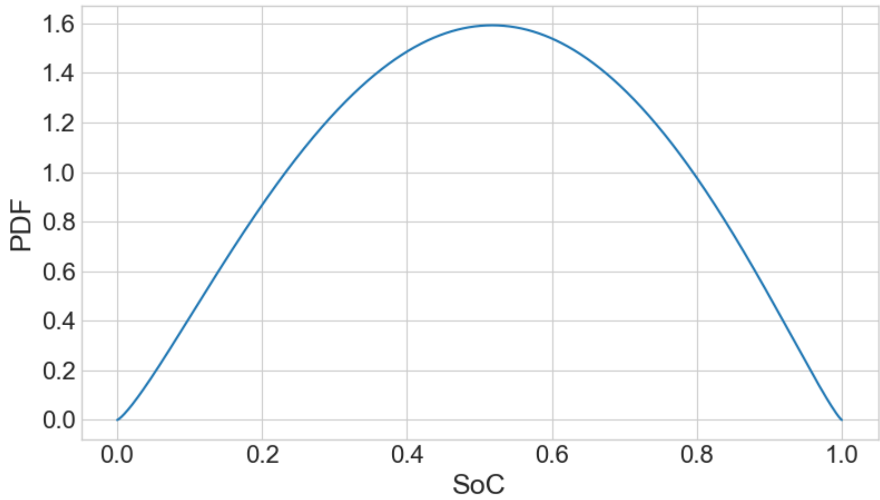

Figure 3.11: Beta distribution ($\alpha = 2.27$, $\beta = 2.18$) used for modelling vehicle state of charge on arrival at destination charging infrastructure

Parking Duration

The length of time the EV spends in the car park was modelled by a Poisson distribution, a method taken from [131] which uses the distribution to model an analogous quantity – the length of stay of patients in hospital beds. The distribution used for this work is the same as that in (3.2), with the mean service time T set depending on the type of amenity being analysed.

Other EV Parameters

The other EV parameters – battery capacity and arrival time within the hour – are simulated in the same way as in Section 3.4.

3.5.4 EV Fleet Charging Algorithm

For the j^{th} minute of the day, $j \in \mathbb{N}, 0 \leq j < 1440$, and the c^{th} car in the car park, $c \in \mathcal{C}_j$, where $\mathcal{C}_j$ is the set of cars in the car park at the start of minute j, Θ_j is the total energy requirement of all cars in the car park at the beginning of the j^{th} minute (3.8).

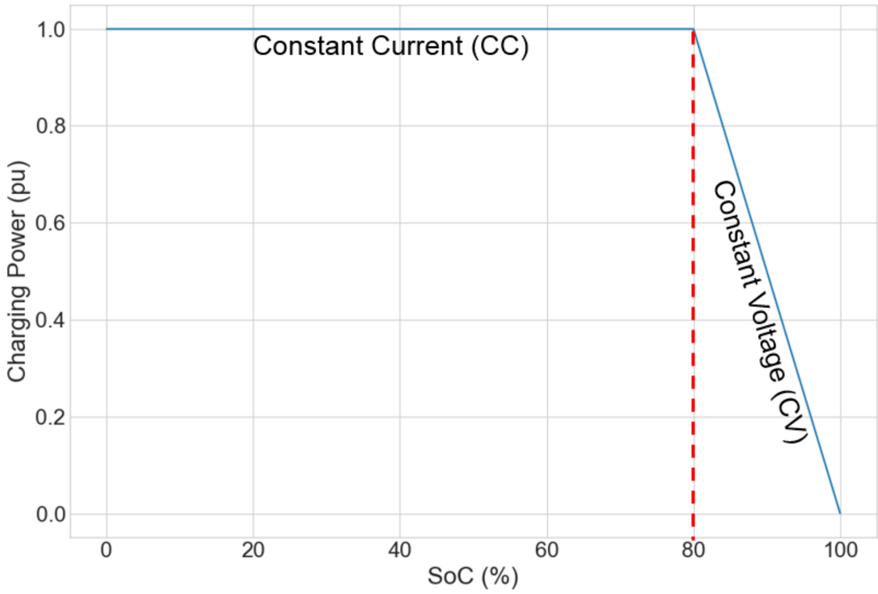

Figure 3.12: Charging profile used for destination charging simulation

$$\Theta_j = \sum_{C_j} (1 - S_{c,j}) C_c \tag{3.8}$$

where $S_{c,j}$ is the c^{th} car's SoC at the start of the j^{th} minute and C_c is the c^{th} car's battery capacity.

$\Psi_{c,j}$ is the potential charge rate of the c^{th} car at the start of the j^{th} minute, i.e. the maximum charge rate it could draw if unconstrained, is (3.9).

$$\Psi_{c,j} = \frac{(1 - S_{c,j}) C_c}{\Theta_j} P^G \tag{3.9}$$

where P^G is the total available grid capacity (see Figure 3.10).

The power drawn by each EV in each minute is then subject to a series of constraints. Firstly, the maximum power the EV battery can accept is limited by the charge profile P^B, taken from [82] (Figure 3.12). Below an SoC of 80%, the charger will operate in constant current mode and the power is not limited. Above 80%, the power drawn will linearly decrease to zero at 100%. Note that this linear decrease of charging power with respect to SoC sets the exponential behaviour with respect to time as seen in Figure 2.6.

The power draw is also limited by the rating of the converter, P^C, and the maximum power the EV can draw, P^{EV}. This is assigned as either 50 kW, if the car's battery capacity is less than 60 kWh, or 120 kW if the car's batter capacity is over 60 kWh in common with analysis in Chapter 2 (see Table 2.2).

$\psi_{c,j}$ is the actual charge rate of the c^{th} car in the j^{th} minute, given by (3.10).

$$\psi_{c,j} = \begin{cases} \Psi_{c,j}, & \Psi_{c,j} \leq min(P^B_{c,j}, P^C, P^{EV}_{c,j}) \\ min(P^B_{c,j}, P^C, P^{EV}_{c,j}), & otherwise \end{cases} \tag{3.10}$$

The SoC of the c^{th} vehicle at the beginning of the next $(j+1)^{th}$ minute is then calculated in (3.11), where Δt is the timestep (1 minute).

$$S_{c,j+1} = S_{c,j} + \frac{\psi_{c,j}\Delta t}{C_c} \tag{3.11}$$

If a car arrives such that the size of $\mathcal{C}_j$ is greater than the number of charging spaces, the car joins a queue. The queue continues to grow in length as more cars arrive, until any cars within the charging spaces leave. When that happens, a car is picked at random from the queue to join the charging space to reflect real queuing processes in car parks. The time at which that car begins charging is adjusted accordingly, and it is assumed that its parking duration and all other parameters remain the same.

3.5.5 Characterisation of EV Charging at Gym Car Parks

Monte Carlo Simulation of Amenity Activity

The Google Maps Popular Times data was fetched for a sample of 2,221 gyms in and around major GB population centres. According to [132], this represents around a third of the total number of gyms in the UK. Based on this data, an MC-based approach was used to form CDFs of the percentage popularity for each hour of the day. From this, a Monte Carlo (MC) approach was used to derive a simulated popularity profile for any day of the week. This can then be translated to an arrivals profile using the same method as in Section 3.4.2 for a specified number of EV charging spaces. The simulation was run for 10,000 trials based on all gyms in the sample, for a 100-car capacity EV charging car park with a 2 MW grid capacity and 50 kW converter rating.

Results

Results are presented in terms of a CDF plot for simulations based on the sample of gyms for Monday (Figure 3.13) and Saturday (Figure 3.14) popularity data.

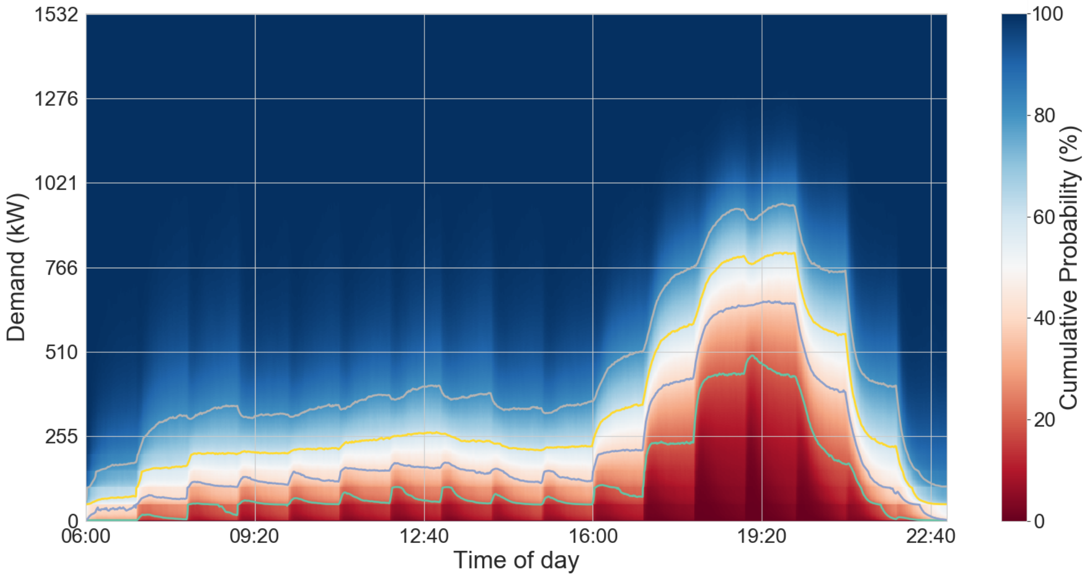

Figure 3.13: Cumulative distribution function for Monte Carlo simulation of EV charging at gym car park from Monday popularity data

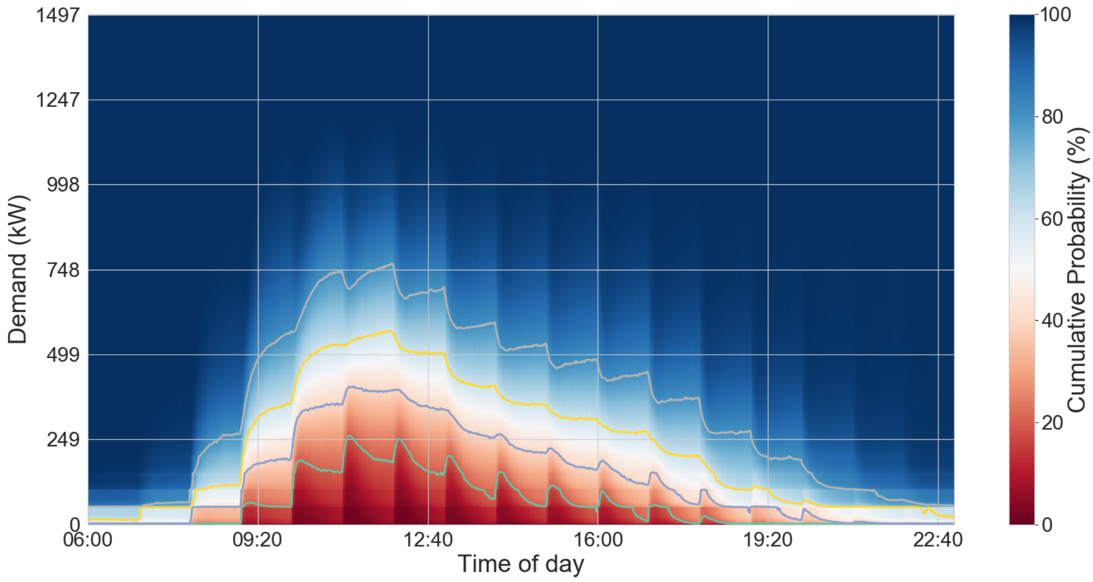

Figure 3.14: Cumulative distribution function for Monte Carlo simulation of EV charging at gym car park from Saturday popularity data

As exemplified by Figures 3.13 and 3.14, the weekday demand profile for gym-based EV charging is most likely to peak in the evening around 18:00-20:00 whereas the (lesser) weekend charging demand is most likely to peak in the late morning/noon around 10:00-13:00.

The method demonstrated provides a probabilistic evaluation of the likely EV charging demand at a given type of amenity. For example, Figure 3.13 shows a 20% probability that the charging demand peak on a Monday will be greater than approximately 1000 kW between the hours of 18:00-20:00. This temporal analysis could be invaluable in assessing the potential of smart grid technologies to provide a better utilised electricity network, exploiting the potential diversity between EV charging in different locations and between EV charging and the pre-existing network demand.

3.5.6 Case Study: Transmission-Connected EV Destination Charging at Large GB Shopping Centre

Braehead is a large shopping centre and leisure complex in Glasgow, Scotland. Due to its proximity to the M8 motorway and its total of 6,500 car parking spaces, it has the potential to serve as a significant destination charging location. Its proximity to local transmission infrastructure means that it could be connected directly to a GSP, affording the charging car park a large grid import capacity.

From [133], it is reported that customers spend an average of 134 minutes there. Setting T as 134 minutes in 3.2, the Google Popular Times data can be used with the fleet charging algorithm (Section 3.5.2) to produce an expected demand profile for the period of interest (i.e. when the shopping centre is open).

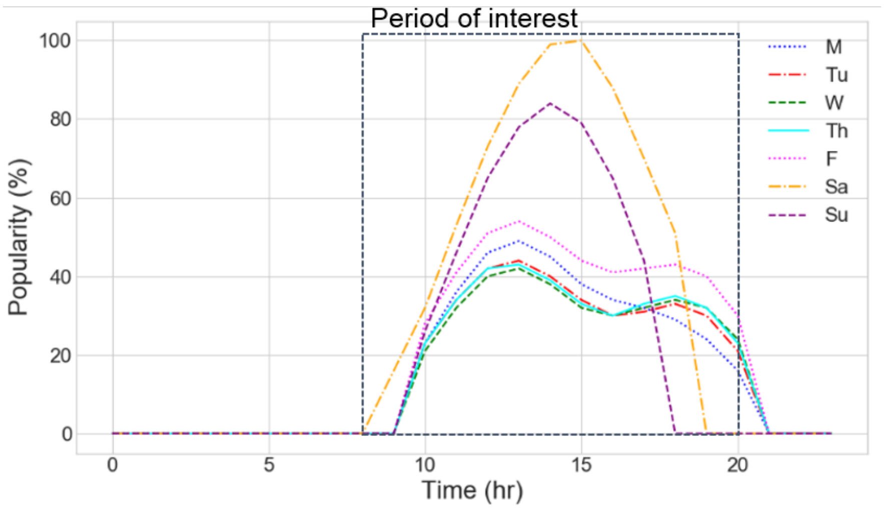

Figure 3.15: Google Maps Popular Times data for Braehead shopping centre retrieved on 20th August 2019

Two values for P^G and three values for P^C were used to examine the effect of the car park parameters on peak demand and service provision, as shown in Table 3.1. Combining the values gives six combinations of variables, for which the variation in demand profile (Figure 3.16) and service provision (Figure 3.17) are shown.

Table 3.1: Values of grid and converter capacity used for case study of Braehead shopping centre EV charging infrastructure

Parameter	**Low**	**Medium**	**High**
P^G	10 MW	–	25 MW
P^C	10 kW	20 kW	50 kW

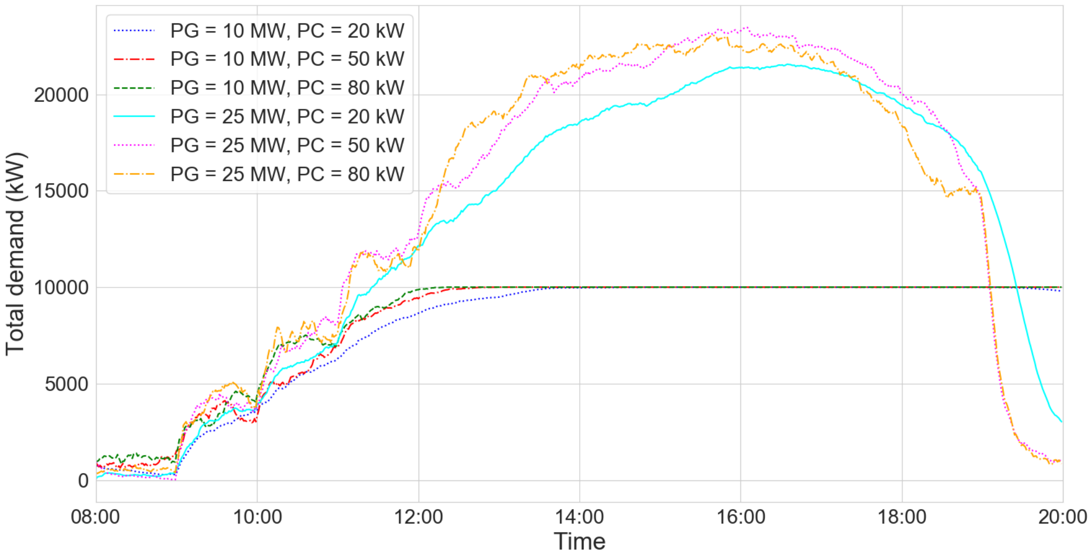

Figure 3.16: Variation of demand profile expected in charging demand at large GB shopping centre with varying grid and converter capacities

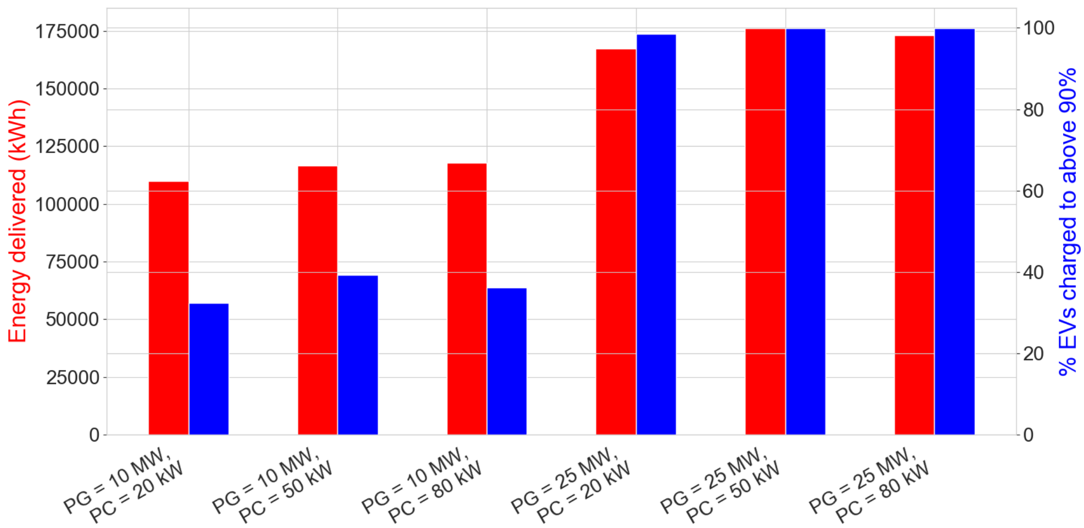

Figure 3.17: Variation of service provision expected at charging car park at large GB shopping centre with varying grid and converter capacities

Figures 3.16 and 3.17 show that only a P^G of 25 MW allows fully unconstrained charging on a Saturday and, with sufficient P^C, allows all vehicles to charge to at least 90% SoC during their stay. As the grid capacity is reduced, the service provision and peak demand are reduced, but the time spent at the maximum demand increases, with the profiles in Figure 3.16 for a P^G of 10 MW at their upper limit for up to eight hours of the day.

The energy delivered (kWh) throughout the Saturday simulated is shown in Figure 3.17. Taking the average tariff for a non-domestic customer as 10.8 p/kWh [134], the charging car park owner could make a profit of around 9 p/kWh if they were to match the 20 p/kWh rate currently offered by multiple public charging networks in the UK [40]. Multiplying 9 p/kWh by the energy delivered (kWh) enables a potential Saturday revenue to be calculated: this varies between around £8,900 for a P^G of 10 MW and a P^C of 10 kW to £15,900 for a P^G of 25 MW and P^C of 50 kW. By integrating the curves in Figure 3.15, it can be found that the Saturday footfall accounts for approximately 21% of the total. Therefore, it can be supposed that the potential annual revenues from such a scheme could be in the region of £2-4 million per year. This simplistic economic analysis ignores converter losses and equipment downtime as a result of maintenance, but enables the quantification of the potential inflows of finance from such charging schemes and provides grounding for more robust business case analysis.

From this potential revenue, the charging infrastructure owner would have to finance infrastructure capital, operation, maintenance and any connection reinforcement costs made necessary by the increase in demand. These costs would vary by grid and converter capacity, as would the potential revenue: therefore, the sizing of car park infrastructure in such applications will likely be a question of economics. If the charging is to provide an extra revenue stream to the amenity, then maximum service provision at an optimal trade off with infrastructure cost may be sought. However, if the amenity is using EV charging as a 'loss leader' (i.e. purely to encourage more visitors) then a lower service provision may encourage customers to stay longer, which may be preferable to the owners of some amenities, such as shopping centres.

3.5.7 Discussion

This section has presented a characterisation of likely demand profiles of destination charging at popular amenities has been presented. It has been applied to a generic gym based on a sample of gyms in GB and also to a case study of a real shopping centre, to explore the difference in likely EV charging demand at different types of amenities and the effect of infrastructure specification on service provision.

It is shown that EV destination charging demand is likely to vary significantly depending on the type of amenity at which it is installed and the day of the week. For example, if charging is installed at a gym then the weekly peak is expected to occur on a weeknight evening, whereas if charging is installed at a shopping centre then the weekly peak is expected to occur on a weekend afternoon. It is proposed that this method could be used to investigate the likely temporal variation between charging at different destination charging stations that may be drawing power from the same portion of the electricity network. Based on this, modelling can be developed in which smart grid technologies and novel tariff arrangements can be assessed in their potential to enable an electricity system fit for the electrification of personal transport at the lowest possible cost to both the EV user and the energy consumer.

The governing assumption in this work has been that the rate of arrivals in EVs to these destinations is proportional to the rate of arrivals of individuals with smartphones and the Google Maps application installed. While this may be reasonable in some circumstances, the approach raises some wider questions. It was found in Chapter 2 that individuals who lack access to parked charging are likely to be faced with significant inconvenience if they switch their ICV for an EV. Following this line of thought, the provision of plentiful charging infrastructure at destinations such as gyms, cinemas and supermarkets would seem to be a 'leveller' with regards to the mobility inequality between individuals with home charging and those without that may arise from the shift of EVs. However, it also risks increasing car dependency; a journey to a gym or shopping centre that may have been made by public or active transport could be replaced by a car journey if the driver is given the incentive of free/low cost charging when they get there. As further discussed in the Epilogue of this thesis, the electrification of private road vehicles and the associated provision of public charging infrastructure may be at odds with the wider decarbonisation effort if it serves to increase the amount of traffic on the road.

3.6 Chapter 3 Conclusions and Further Work

This chapter has presented a method for the characterisation of EV charging demand at public places – both in terms of destination charging while drivers visit destinations such as shopping centres, supermarkets and gyms and en route charging, in which drivers visit charging stations analogous to petrol stations with the sole purpose of replenishing the energy storage content of their vehicles.

From reviewing literature on the subject, it was found that there is a growing interest in modelling likely EV charging demand based on the frequency at which people are likely to visit the locations at which charging infrastructure is likely to exist. It was found that there was a gap in the research using large-scale mobility datasets such as that in the Popular Times feature in Google Maps. As EV charging becomes more commonplace in public places and as businesses continue to install charging infrastructure to attract a greater throughput of customers, the methods presented in this chapter could be valuable to network owners and policymakers so that efficient systems that allow for the electrification of transport can be developed.

To improve the accuracy of the model presented in this paper, the following pieces of further work are suggested:

1. A sensitivity study of the effect of the assumed distributions of EV battery capacity (Figure 3.6) and SoC on arrival (Figures 3.7 and 3.11) on the resulting demand from both public destination and en route charging

2. A sensitivity study of the effect of a greater timestep in the fleet charging simulation (Section 3.5.2) on the resulting charging demand.

3. Modelling of how the usage of destination charging installations at different amenities may interact with one another and how they might interact with other modes of EV charging, e.g. domestic and rapid charging. By building a robust system of modelling for this, insights on the overall impact to the electricity network from EV charging can be given and this can be used to form recommendations as to the policy of the development of EV charging infrastructure.

Fundamentally, the methods presented in this chapter represent a 'system view', in that it assumes that an instance of charging infrastructure (for example, in a supermarket car park) will be well-suited to the local market conditions in that its occupancy will be proportional to the occupancy of the business at which it is situated. In doing so, it assumes that an EV that visits a series of locations is equally likely to charge at any one of those locations as its visit is captured in the data (or any such mobility data) used for this method. In reality, a vehicle may opt to charge at a specific subset of those locations that maximises convenience or minimises cost. Therefore, analysis is required that takes into account the series of trips made by vehicles and the subsequent set of charging trips that they will carry out. This is explored further in Chapter 4.

Chapter 4

Modelling the Impact of Uncontrolled Electric Vehicle Charging on Residential Distribution Networks

4.1 Introduction

4.1.1 Motivation

In Chapter 2, it was found that if individuals are to experience a level of convenience using an EV that is comparable with using an ICV, then access to charging at home is likely to be very important. Furthermore, the Department for Transport have predicted that the majority of EV charging will be carried out at home [135]. However, concerns have been raised by network owners, policymakers and government about the impact of widespread EV uptake and the subsequent charging at peoples' homes, where the capacity of existing distribution networks may not be able to cope with the increase in demand [22–25, 135].

Analysis presented in this chapter serves two purposes. Firstly, by establishing the likely impact of uncontrolled domestic EV charging on distribution networks, the concerns of the above parties can be investigated. Secondly, by quantifying the likely charging patterns of EV users, the foundation can be laid for the analysis of any controlled charging, as this can only be done with an understanding of the likely charging requirements of EV drivers. This is further explored in Chapter 5.

4.1.2 Contribution

This chapter seeks to establish the likely impact of uncontrolled domestic EV charging on residentially-dominated distribution networks.

A sociotechnical modelling methodology, combining electrical, geographical and socioeconomic datasets, is presented to model two real distribution networks generated from geographical information systems (GIS) data provided by SP Energy Networks, the relevant distribution network operator (DNO) for the location being studied. The network GIS data are cross-referenced with geospatial UK Census and Scottish Index of Multiple Deprivations (SIMD) data, such that the resulting network models have not only electrical properties, but key demographic properties: each network endpoint has an associated probability distribution for each household at that endpoint being assigned a particular value of a given socioeconomic indicator (e.g. number of vehicles at household; employment type of household reference person). This is further explained in Section 4.3.

It is discussed on the basis of a literature review (Section 4.2) that there are two reasonable methods of simulating EV charging demand on distribution network models – i) using publicly available EV trial data and ii) deriving likely charging habits from ICV-based travel data – and that there are merits to both. As such, both methods are demonstrated (and compared) in this chapter. Firstly, data from *My Electric Avenue* (MEA), a real EV trial conducted around various parts of the UK between 2013 and 2015, is statistically analysed and applied to the network using an MC-based approach – in effect, it is assumed that every vehicle in the network will charge according to a set of probability distributions generated from analysis of the MEA data. Secondly, a set of two models for deriving charging schedules from the car-based NTS travel diaries used extensively in Chapter 2 are presented (one in which drivers seek to minimise their number of plug-ins, and one in which drivers will always plug in upon arrival at home regardless of their SoC), in order to encapsulate the potential variation in individuals' charging behaviour given a fixed set of travel requirements.

A key contribution of the work presented in this chapter is that for the latter method, these NTS travel diaries are disaggregated on the basis of two key demographic indicators: employment type (e.g. 'employed', 'self-employed') and means of travel to work (e.g. 'car driver', 'train')[1]. By matching these travel diaries and resulting charging schedules with a fleet of vehicles instantiated in the network according to a MC-based simulation in which the probability distributions of the socioeconomic indicators of households at each endpoint are sampled over a number of trials, the likely variation in EV charging demand is reported.

This approach is used as a baseline for the analysis of the effect of the following three variables on resulting charging demand:

1. **Driver charging behaviour**, by performing the study using the two models for deriving charging schedules from NTS travel diaries

2. **Demographics**, by performing the study on two distinctly different – in terms of the socioeconomic makeup of the area – residential networks in the Southside area of Glasgow

3. **EV parameters**, by performing the study using different combinations of battery capacity, charger power and level of access to charging

The results presented in this chapter are summarised and recommendations are made based on the findings in Section 4.9.

[1]Although all trips in the NTS travel diaries are made by car, the nature of these journeys are found to be different if the driver uses their car to get to work or if they use some other means. This is further explored in Section 4.6.2.

4.2 Literature Review

4.2.1 Charging Start Times and Energy Requirement

In order to establish an EV charging demand, one must establish a rate of arrival/plug-in of vehicles, a rate at which the vehicles can charge (i.e. a charger power) and either an energy requirement to be met or a fixed period for which the vehicles are assumed to be charging. The methods by which this is done are varied across the literature, though can be divided into three categories as described below.

Fixed assumptions

This category of methods is the most simplistic of those discussed. In some studies [136, 137], it is assumed that all the vehicles arrive at a given time with a single, fixed energy requirement: in both of the above works, it is assumed that all vehicles arrive home and seek to charge at 6 pm at a fixed rate for a given time period. In [138], although arrival times of vehicles are split between three 'charging periods' proposed from the analysis of travel data, all vehicles are subject to the same energy requirement based on a fixed daily driving distance. Other studies, such as [139] and [140], assume that a proportion of vehicles are connected to the network at different times of the day (e.g. a certain proportion are connected during a peak time, and another – usually lesser – proportion are connected during an off peak time). Both [139] and [140] assume a fixed, constant charging rate for all vehicles during a given period.

While these simplified assumptions can provide a necessary base on which to develop other methods – such as managing charging demand [137, 138], simulating the 'worst case' effects on endpoint voltage and line loading [140] or investigating the effect of network topology on the impact seen [139] – they tend to be pessimistic: the work presented in this chapter suggests that it is very unlikely to have all the vehicles in one area arriving and charging simultaneously, and therefore designing a network on the basis of such an assumption would likely lead to over-engineering and under-utilisation. In [141], the authors present a simulation tool for the departure, driving behaviour and arrival (and subsequent charging requirement) for a synthesised fleet of vehicles made up of different archetypes (e.g. commuter vehicles, 'family' vehicles, taxis etc.) While the spread in results does eliminate some of the pessimism associated with the assumption of all vehicles arriving at a given time, it is not based on any particular real-world dataset pertaining to the likely mix of vehicles in a given area.

Use of Travel Survey Data

The analysis of travel survey data – that is, self-reported data pertaining to the location, distance and duration of individuals' trips – can be used to simulate the arrival time and energy demand of a fleet of EVs, the governing assumption being that if ICVs were replaced with EVs, the trips made by the individuals driving the vehicles would be unchanged. [142] uses results from a US-based travel survey [143] to return probability distributions of the arrival time of vehicles following a day of driving. However, although the start times of charge events are based on real data, the energy requirement is driven by the simple assumption that vehicles begin a charging event with a battery SoC sampled from a Gaussian distribution centred on 50%. [144] and [145] return distributions of the time at which the EV arrives at home (and hence starts charging) and the daily distance driven (and hence the energy required from charging based on a fixed rate of consumption) from statistical analysis of the UK Time Use Survey (TUS) and the US National Household Travel Survey (NHTS) respectively. [146] uses Origin-Destination analysis to set origin and destination zones of each EV's journey based on statistical analysis of travel survey data; the distance between the two is sampled from a Gaussian distribution about the straight line distance between the centroids of the zones. [147] applies a clustering technique to results of the Dutch travel survey (Mobiliteitsonderzoek Nederland) to produce 25 archetypal driving behaviours, from which probability distributions of the arrival time and charging energy requirement are returned. [148] uses a Gaussian Copula method to tie together the separate distributions of the time a vehicle leaves home, the time a vehicle arrives home and the overall distance it travels during the day (from which the charging energy requirement is derived) from the same Dutch travel data as [147].

While they capture the variation in real driving behaviours and contribute to a more realistic impression of the demand of EV charging, the works discussed above [142, 144–148] only consider one driving day: it is assumed that every vehicle can (and does) charge once per day regardless of the distance it travels. Conversely, [149] uses data from the week-long US NHTS to simulate EV charging behaviour on the basis of every travel diary in the dataset, hence giving a week-long charging demand profile that reflects day-to-day driving behaviour.

All the papers discussed in this section assume that when a vehicle arrives at a location where it can charge, it will always charge. While this could well be a common course of action for EVs with smaller battery capacities that must be charged after a typical day of driving, as battery capacities continue to increase with the evolving EV market the likelihood of EV drivers taking every opportunity to plug in could be expected to decrease. The work presented in this chapter provides modelling of drivers' likelihood of charging to evaluate the effect of this crucial assumption on the resulting electricity demand from EV charging.

Use of EV Trial Data

Within the last decade, publicly funded EV trial projects have been completed with the aim of providing an insight into the driving and charging habits of EV users. Several works have been carried out that use the results of these trials to derive probability distributions of charging start time and energy requirement. In [150], data from the British EV trial *Plugged In Midlands* is used as a basis for clustering of EV demand profiles and a risk assessment of the violation of network limits following the electrification of a fleet of private vehicles displaying the same charging behaviour as in the trial. In [151], data from Newcastle University's *SwitchEV* project is used to build a stochastic simulation of the impact of EV charging on a real distribution network feeder. [152] uses an unnamed Irish EV trial dataset to simulate charging profiles of a fleet of EVs that may have access to charging at a variety of locations over the course of two days, thus capturing the effect of charging events on subsequent driving and charging behaviour.

EV Trial Data vs Travel Survey Data

While the use of EV trial data can highlight observed behaviours in EV charging patterns, one of its key problems is that the data is generally tied to a particular set of technologies and/or individuals. For example, the trial datasets used in [150–153] concern vehicles with battery capacities in the range 16-24 kWh and 'slow' charging of 3-4 kW. The rapid changes in the EV market in terms of battery capacity and charger power as discussed in Section 1.2 mean that these datasets can become out of date. Furthermore, the trials are generally made up of early technology adopters and often (as is the case with the MEA trial) are constrained to individuals who have off-street parking or are guaranteed to drive at least a certain distance during the trial, hence skewing the set of driving behaviours which will come out of any analysis using these datasets.

On the other hand, it has been shown that the adoption of EVs has a significant impact on the behaviour of drivers [69, 70]. Furthermore, the application of ICV travel data to a fleet of EVs may not be feasible, given the generally lower driving range of EVs. In this respect, using EV trial data holds a distinct advantage over the use of travel data.

Due to the respective merits of using both EV trial data and travel survey datasets to model EV charging and its impact on the distribution system, the work presented in this chapter shows the analysis of the impact of EV charging using trial data from the MEA EV trial and also from a simulation built from the NTS dataset, which can be used to examine the impact of various parameters (battery capacity, charger power and level of access to charging at different locations) and charging behaviour (an individual's likelihood of charging given an opportunity to do so) on the resulting loading on the distribution network.

4.2.2 Distribution Network Impact

The majority of works in the literature focus on integrating EV demand models with distribution networks, where they are expected to cause the greatest impact [154]. With the exception of [148–150, 152], all of the other works reviewed [136–142, 144–147, 151, 153] involve some level of simulation of EV charging and the superposition of this demand onto a model of a distribution network.

All of the works in [136–138, 142, 145, 147] use simple, generic distribution networks (for example, one of a number of IEEE distribution test feeders [155]) to model the impact of EV charging. While the use of these generic test feeders can provide a valuable base to develop and test a model, it is suggested that the area-specific, often historical design features of electrical networks are likely to have a significant effect on the impact seen by the network from EV charging and therefore the use of generic test feeders is prone to misrepresentation of the issues that may arise in real networks.

To this effect, there are works that have looked to simulate EV charging demand on real networks. [140] presents analysis of part of a real distribution network, though it only consists of a single LV feeder serving 135 households. [139] presents work on a much larger area of a real LV network serving over 6,000 customers and [141] uses a representation of a network serving over 10,000 endpoints on the Danish island of Bornholm. In using such large networks, the latter two [139, 141] assign EV loads to households deterministically. In contrast, [151] presents MC analysis of EV charging on a real GB distribution network serving 288 households which can be used to show the variation in expected charging behaviour.

While the electrical characteristics of real distribution networks are captured in all the works discussed [139–141,151], the socioeconomic characteristics are left out: simple, fixed assumptions are made as to the rate of EV penetration in the networks and there is no disaggregation of domestic consumption or travel habits within a population. In the work presented in this chapter, the socioeconomic and electrical characteristics of a real distribution network are merged, as to develop a network and population-specific simulation of the impact from EV charging.

4.2.3 Integration of Socioeconomic Factors in Distribution System Modelling

There is no such thing as a typical electrical network, nor a typical set of energy consumers. It has been documented in [156–158] that domestic energy usage is dependent on several factors, including (but not limited to) income, age, floor area, household size, bedroom number, occupant age, social class, employment status and tenure. Travel habits are similarly influenced; [159–161] all provide quantitative results on how income, employment status and geographical location impact travel habits of individuals.

Out of the works discussed in this section, only [149] provides disaggregation of travel behaviour via analysis of the US NHTS to present differences in driving habits and expected charging load from a fleet of plug-in hybrid vehicles on the basis of age, income and location (urban/rural). While the study produces results to suggest that there is a significant variation in the resulting charging demand from a base of varied individuals with varied travel habits, there is no application of this demand to a network and therefore no investigation on how this variation in charging demand is seen by the network.

4.3 Sociotechnical Model to Evaluate the Impact on Uncontrolled EV Charging on Distribution Networks

4.3.1 Overview

This work presents a sociotechnical model to join together the electrical and socioeconomic elements of an electricity network and the individuals who are served by it. The model takes electrical and geographical data from a set of distribution network GIS data as provided by SP Energy Networks, the DNO who operate the network in question. The socioeconomic data used to characterise the households and individuals who are served by the network are taken from three sources: the 2011 UK Census, the SIMD and a building classification dataset – which was an outcome of SP Energy Networks' innovation project *Network Constraint Early Warning System* [162].

To provide a level of base domestic demand (before the introduction of EVs), an established domestic demand tool is used as described in Section 4.4. The tool produces a series of demand profiles for a set of households which, using the socioeconomic datasets stated above, is used to produce a detailed representation of the pattern of domestic electricity demand in a given distribution network.

As already mentioned, two methods of simulating the likely impact of EV charging on distribution networks are presented. Firstly, in Section 4.5, charging data from the MEA trial [163] is statistically analysed to produce likely demand profiles of EV charging. Secondly, in Section 4.6, charging schedules are derived from NTS travel diaries, which are then used to produce likely demand profiles of EV charging.

Figure 4.1 shows a map of the processes carried out to conduct analyses using the network models presented, highlighting key datasets used.

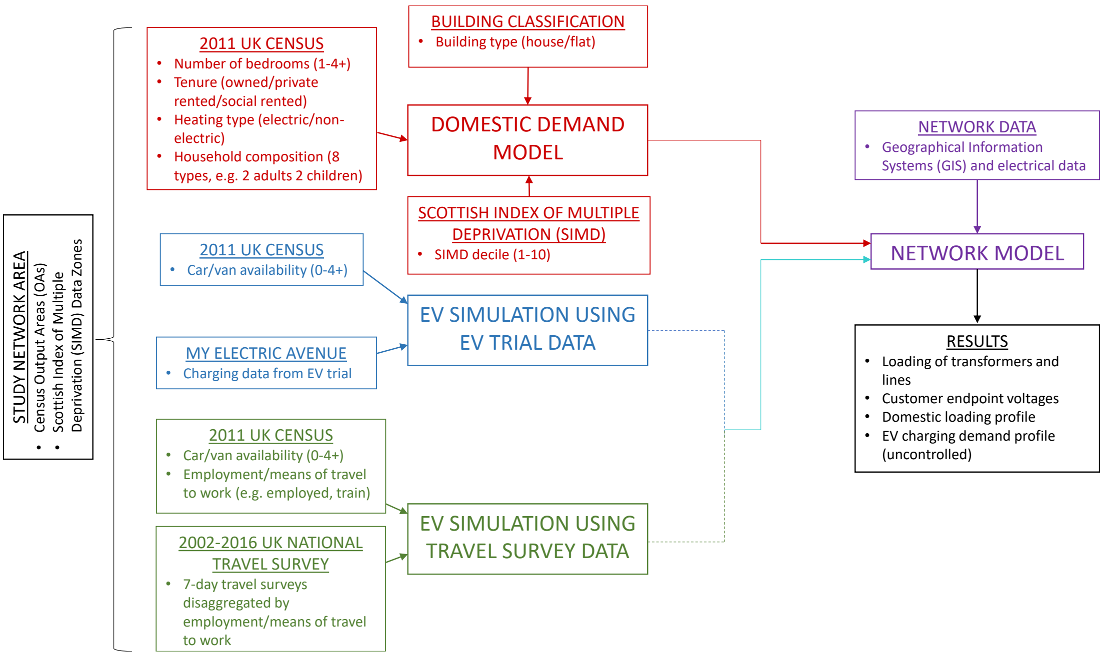

Figure 4.1: Process map showing how specific datasets are input into domestic demand model and EV charging simulations to produce results from network model

This section presents the method by which the electrical, geographical and socioeconomic datasets are joined to make the sociotechnical model to evaluate the impact on uncontrolled EV charging on distribution networks.

4.3.2 Study Distribution Networks: Pollokshields and Gorbals, Glasgow Southside

The two networks examined are in the Southside region of the city of Glasgow, Scotland. The area is mainly residential, with a diverse mix of housing ranging from large mansions to tenement flats. As could be expected, the individuals who reside in the area are of diverse characteristics, which as previously discussed is likely to have an influence on the domestic and EV charging demand in the area.

Both parts of the distribution network are identified in Figure 4.2.

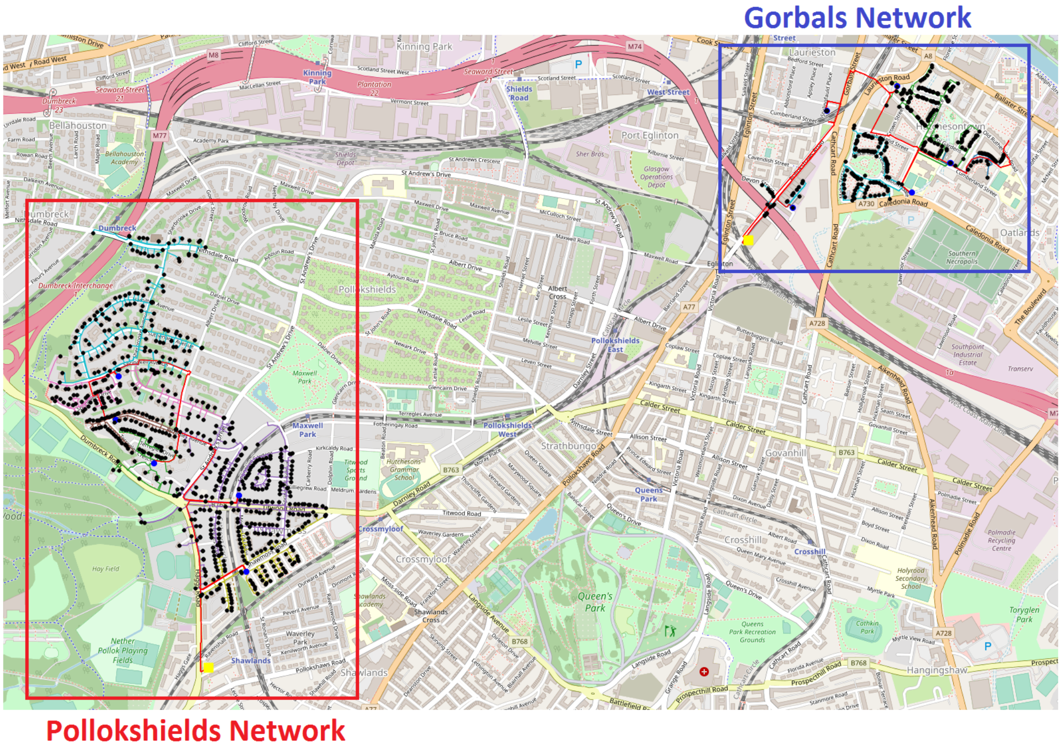

Figure 4.2: Glasgow Southside distribution networks – Pollokshields and Gorbals – plotted over OpenStreetMap data showing location of network assets

Whereas the area covered by the Pollokshields network is characterised by suburban avenues with large Victorian mansions and post-war detached houses, the area covered by the Gorbals network represents a newly re-developed and historically deprived area of the city, characterised by higher-density housing in the form of small dwellings and purpose-built flats. The differences in accommodation and population characteristics are analysed in depth in Section 4.7, though the difference in housing density is immediately visible from Figure 4.2: although the Gorbals network is shown to cover a smaller area than the Pollokshields network, it supplies electricity to 1522 households compared to 857 households served by the Pollokshields network.

Figure 4.3: Residential parking in Pollokshields network (left) and Gorbals network (right) – imagery from Google Maps

These areas were chosen for study because while they represent significantly different spreads in accommodation types and population characteristics and hence likely significant different electricity demand and travel patterns, both areas have a large availability of dedicated resident parking spaces (either private driveways or reserved resident parking spaces in designated bays), at which it would be reasonable to assume EV charging infrastructure could be installed. Thus, it is assumed that any EVs within either network have the opportunity to charge at home. Figure 4.3 shows archetypes of dedicated residential parking in the two study network areas.

4.3.3 Network Data

Each network consists of a primary (33/11 kV) transformer, a HV (11 kV) feeder leading to a series of secondary (11/0.4 kV) transformers and a series of LV (0.4 kV) circuits leading to customer endpoints. In Figure 4.2, yellow squares represent primary transformers, blue circles represent secondary transformers and black points represent customer endpoints. HV circuits are represented by red lines and LV circuits are coloured by circuit (and hence electrical connectivity).

The network data includes line data (length, resistance and reactance per km, parent circuit, rating), bus data (voltage, number of meters connected) and transformer data (model, rating and tap settings for the primary). Load switches are set in the network at their nominal position as in the real network. Both primary transformers have on-load tap changers (OLTCs), with automatic voltage regulators (AVRs) that can increment their tap settings by 1% between a minimum of -16% and a maximum of +5% to attempt to maintain their LV busbar at a given voltage. In this case, this target voltage is assumed to be 1 per unit (pu)[2]. The secondary transformers have adjustable tap settings, but this must be done manually while disconnected – not a workable option for real time network operation. As secondary tap settings are not known, in this study all are fixed at 0%.

It is assumed that three phases are balanced and thus a three phase system is modelled as one of a single phase with an endpoint nominal voltage of 400 V. While the DNO do not have information on how heavily individual phases are loaded, a piece of further work could be done on investigating the effect of unbalanced phases by remodelling the network as a 3 phase system.

A set of scripts was developed using the Geopandas Python module [164] to generate a set of Geodataframes from the GIS and electrical network data, which were originally in the form of .shp shapefiles and .dbf database files. Geodataframes are tabular data structures which contain information (in the form of columns) on a particular object (given by each row). Crucially, one piece of information is the geometry of the object. For the network data, this was in the form of points (busbars) and lines (electrical lines and transformers).

Geopandas was also used to generate Geodataframes of Census Output Areas (OAs), each containing the responses to any census question for around 50-70 households [165], and SIMD data zones, an analogous concept for the SIMD data [166]. With sets of Geodataframes representing both the network data and Census data, these were matched up so that each customer endpoint in the network data was associated with a distribution of responses to every Census question included in this study (Section 4.3.4).

The Python module Pandapower [167], a combination of the data management

[2]This could be increased to mitigate undervoltages in the network arising as a result of increased demand from EV charging, though it would rely on the DNO having reasonable forecasts of the output of any distributed generation in the network, and the consequential voltage rise.

library Pandas and PYPOWER, the Python implementation of MATPOWER, was then used to build electrical network models from the resulting Geodataframes.

Figure 4.4 shows an overview of how electrical and socioeconomic data are combined to build a Pandapower network model.

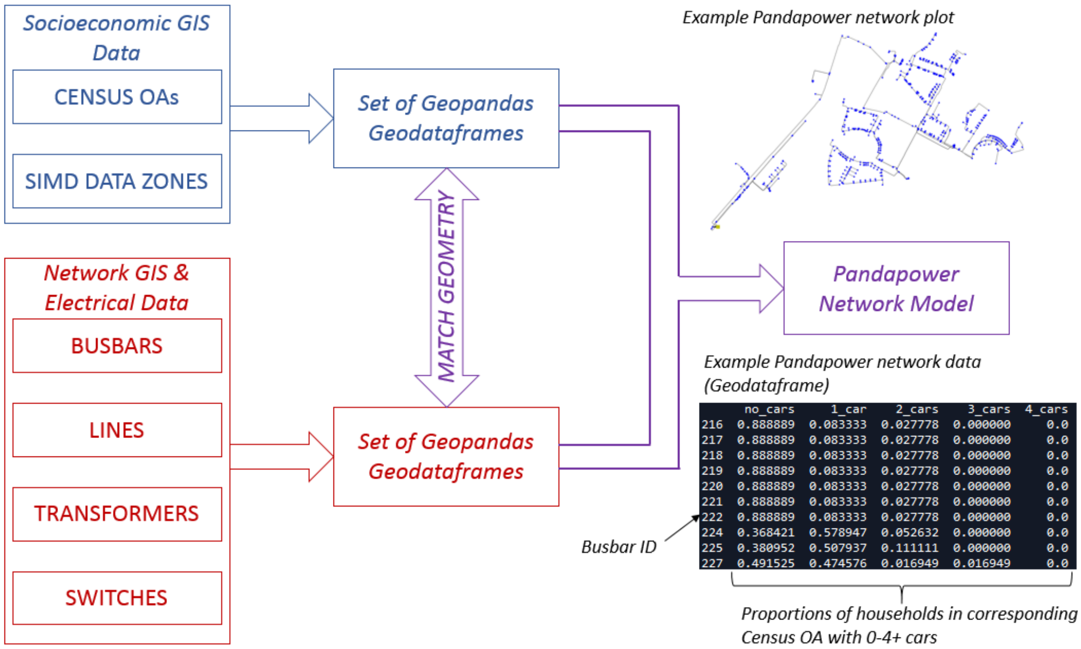

Figure 4.4: Process map showing combination of electrical, geographical and socioeconomic data to build network models

Although the Census data contains responses for every household within each OA, the network might not serve the entirety of a given OA. Therefore, the set of responses are treated as a probability distribution of a response being a given value: for instance, Figure 4.1 shows proportions of households associated with a set of busbars that have access to 0, 1, 2, 3 or 4+ cars at the household. For each run of a simulation, household characteristics are assigned probabilistically using a random number generator. The process used is shown in Algorithm 1, for a given level of EV penetration (0-1, where 1 corresponds to all vehicles in the network being replaced by EVs).

Algorithm 1 Assignment of household characteristics and EVs in study networks

```
for each busbar in the network do
    Return set of households connected
    Return building type from network GIS data
    Return SIMD decile for corresponding data zone
    Return Census distributions for corresponding OA
    for each household at busbar do
        Sample Census distributions
        Return number of bedrooms, tenure, heating type, household composition,
number of vehicles at household
        Assign domestic demand profile from model output (Section 4.4)
        for each vehicle at household do
            Return random number 0 ≤ r1 ≤ 1
            if r1 ≤ EV penetration then
                Instantiate an EV
                Return economic activity/means of travel to work of lead EV driver
```

4.3.4 Household Characteristics

2011 UK Census Data

The last completed census in the UK was run in 2011[3]. Responses to any Census question for all GB OAs are available from the UK Data Service's Infuse service [165]. The questions of interest are detailed in the following list, with any assumptions and processing steps that were taken.

As highlighted in Figure 4.1, the datasets used for the simulations using the MEA and NTS datasets are different. The first four items (number of rooms/number of bedrooms, tenure, heating type and household composition) are taken as inputs to an established domestic demand model used to simulate household electricity demand (this is further explained in Section 4.4). The latter two items (car/van availability and economic activity/means of travel to work) are taken as inputs to the EV charging simulations which, as already mentioned, are two: one which uses charge data from the MEA EV trial (Section 4.5) and one which derives charging schedules based on travel diaries synthesised from the NTS dataset (Section 4.6). In the former, only the first

[3] It is an unfortunate aspect of the timing of this PhD that the last completed UK Census (completed every 10 years) is at the time of writing 8 years out of date. Some demographic shift in these areas could be expected in the meantime; it would be interesting to re-do the analysis presented in this chapter with 2021 Census data upon its release.

of the aforementioned two points (car/van availability) is used, as the socioeconomic characteristics of the MEA drivers are not known. In the latter, both are used; the economic activity/means of travel to work being used as a basis on which to disaggregate NTS travel diaries and apply representative travel habits to vehicles that are associated with particular customer endpoints belonging to particular Census OAs.

1. **Number of rooms/number of bedrooms**

   The domestic demand model (Section 4.4) takes the number of bedrooms as an input to the household demand profile. However, this field is not available in Scottish Census data which uses number of rooms instead. In this question, respondents are asked to give the total number of 'living' rooms not including bathrooms, toilets, halls, landings or rooms that can only be used for storage [168]. Therefore, an assumption was made to map number of rooms (1-9+) to number of bedrooms (1-4+) as follows:

   - 1-3 rooms → 1 bedroom
   - 4-5 rooms → 2 bedrooms
   - 6-7 rooms → 3 bedrooms
   - 8+ rooms → 4+ bedrooms

2. **Tenure**

   The domestic demand model takes tenure as an input as owned, private rent or social rent. However, in the output Census data there are two additional categories; living rent free and 'shared', which in this context means part-owned and part-rented [169]. Under the assumption that living rent free would imply that somebody (perhaps a relative) owned the property and that shared was part-owned, both these categories are included in the owned category when input to the domestic demand model.

3. **Heating Type**

   The domestic demand model takes heating type as an input as electric or non-electric, given that the presence of electric heating would significantly add to a household's demand. The possible responses in the Census data are gas, electric, oil, solid, other, multiple or no central heating. To input the data into the domestic demand model, everything that was not electric was grouped into non-electric.

4. **Household Composition**
   The 'Household Composition' input to the domestic demand model aligns with the 'Household Composition (Alternative Classification)' Census question, which describes the number and age of residents in a household [169], The possible fields are:

   - 1 working-age adult (16-64)
   - 1 retired-age adult (65+)
   - 2 working-age adults (16-64)
   - 1 working-age adult (16-64), one retired-age adult (65+) or 2 retired-age adults (65+)
   - 1 adult, 1+ children
   - 2 adults, 1-2 children
   - 2 adults, 3+ children
   - 3 adults or 3 adults, 1+ children

5. **Car/van availability**
   In this question, respondents are asked to give the number of cars/vans the household has access to (0-4+).

6. **Economic activity/means of travel to work**
   This is a composite of two questions, one regarding the economic activity of the lead household individual (employed, self-employed, unemployed or economically inactive) and their means of travel to work (train, bus, car - driver, car - passenger, work from home, on foot or 'other'). These are then matched up with the NTS travel diaries which have been disaggregated on the same basis. As described in Section 4.6.2, there is no option for being economically inactive in the NTS

individual data. It is assumed that, for the purpose of the assignment of NTS travel diaries, economically inactive is equal to being unemployed and thus all vehicles within a household that is returned as economically inactive are assigned NTS travel diaries from individuals who were unemployed when completing the survey.

2016 Scottish Index of Multiple Deprivation

The Scottish Index of Multiple Deprivation (SIMD) is a measure widely used in Scotland to describe small area concentrations of multiple deprivations. SIMD ranks small areas (called data zones) from most deprived (ranked 1) to least deprived (ranked 6,976) [166]. In the same way as with the Census OAs, the SIMD data zones are overlaid onto the network GIS data to return a SIMD decile (1-10, describing which decile of the 6,976 ranks the zone fits into) for each endpoint in the network, which is then input into the domestic demand model.

SP Energy Networks Buildings Classification Data

As already mentioned, building type classification data exists in the GIS data provided by SP Energy Networks. Rather than representing an area within the network as in the Census and SIMD data, these data are available for each endpoint in the network. The returned value is one of the following: terraced, end of terrace, semi-detached, detached, flat (<20 address points), flat (20-40 address points), flat (40-60 address points), flat (60-80 address points), flat (80-100 address points), flat (100+ address points).

4.4 Domestic Demand Model

It has been established in several studies such as in [170–172] that household energy demand is strongly correlated with occupancy patterns. In this study, a higher-order Markov Chain based household energy demand model by Flett and Kelly from [173,174] is used to synthesise likely demand profiles for the domestic premises in the distribution network. The model simulates household electricity demand based on the active occupancy of households, derived from analysis of the results of the UK TUS, a large-scale household survey that provides approximately 20,000 diaries with a 10-min resolution, with one weekday and one weekend day diary per person, in order to shed light on how people in the UK spend their time [175]. The model is favourable over other widely used demand models such as that in [176] and [177] for this type of community-scale energy analysis due to two reasons, as discussed below.

Firstly, the model in [176] allocates fixed-power loads from appliances whose cycle timing is assumed from broader activity data in the TUS (for example, the 'laundry' activity drives washing machine and/or tumble dryer use). While this is sufficient for certain activities, some are more ambiguous and not so clearly correlated with the use of certain appliances. For example, while probability of the 'food prep' activity is high at breakfast time, use of the oven is generally low [174]. Flett and Kelly's model presents a more sophisticated model that incorporates appliance usage probability distributions from the UK Household Electricity Survey [178] and cycle timing from appliance datasets to reflect different types of power consumption.

Secondly, although models in [176] and [177] do not differentiate between occupants within a household, thereby assuming that occupants conform to an average set of behaviours, the Flett & Kelly model provides disaggregation of household active occupancy based on the categories listed in Section 4.3.4 which, as established by Wilke [179], have a significant impact.

The reader is directed to [173, 174, 180] for detailed information on the domestic demand tool used in this study. Figure 4.5, reproduced from [174], exemplifies the variation in output demand profiles between households of different compositions.

In this study, the model is run for each household (given an established set of household characteristics) for a winter weekday to represent the likely peak in GB domestic demand. The model is run every time the network's households are instantiated (Algorithm 1).

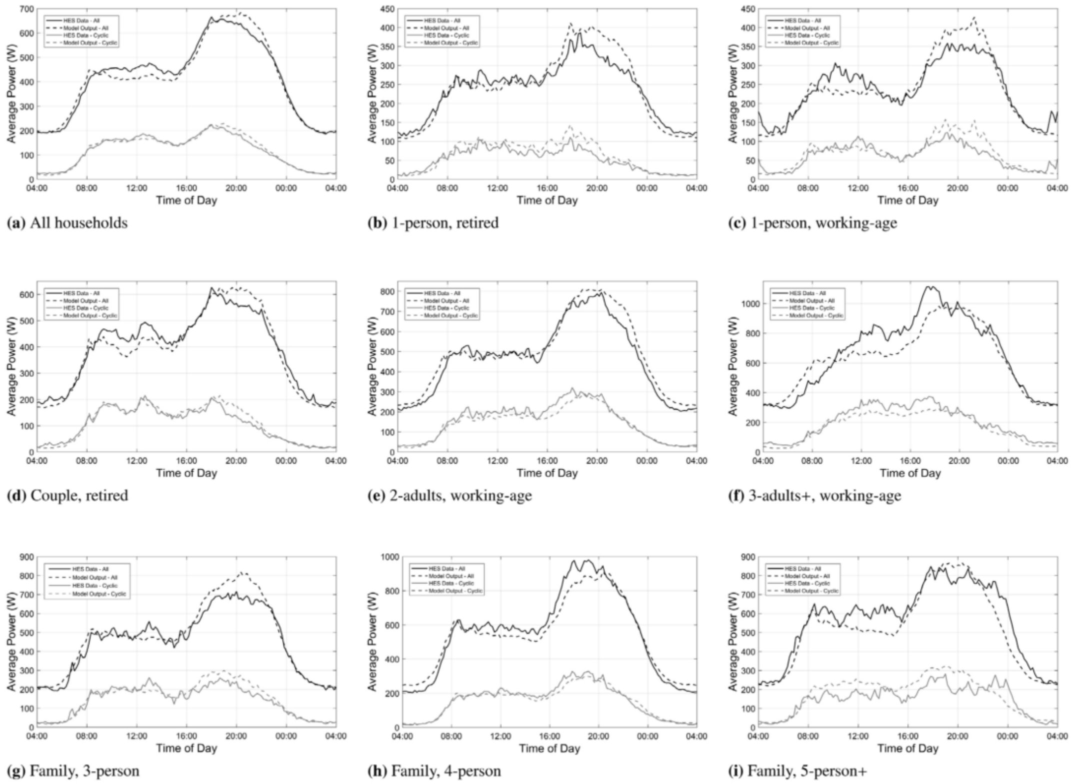

Figure 4.5: Model runs from domestic demand model as used for analysis in this thesis, source: Graeme Flett/University of Strathclyde

4.5 Simulating the Impact of Residential EV Charging on a Distribution Network using EV Trial Data

4.5.1 Introduction

This section presents work on modelling the impact of residential EV charging on the Pollokshields study distribution network using real EV trial data from the MEA trial [163]. Despite the limitations discussed in Section 4.2, the use of EV trial data in simulating the likely effect of EV charging on distribution networks does not require synthesis of charging schedules given travel data (as in Section 4.6) or the associated assumptions as the relevant information is included within the data. Therefore, it is more likely to capture any behaviours which may be specific to the use of an EV which are not seen in the use of an ICV.

4.5.2 My Electric Avenue EV Trial

The MEA EV trial [163] ran from December 2013 to November 2015 across several regions of the UK to capture the likely driving and charging behavior of EV users and hence inform future planning of the energy and transport systems. During the trial, 215 participants each with access to a Nissan Leaf EV (24 kWh battery) and a 3.7 kW private charger had all their trips and charging events monitored.

The trips dataset, once cleaned to remove zero-distance trips (which were logged as a result of the car being started but not driven), comprises 371,293 trips. Within the data is the ID of the vehicle that made the trip, the trip departure and arrival times, the distance covered (km) and the energy consumed (kWh).

The charging dataset, once cleaned to remove zero-energy charging events (logged as a result of the charger being engaged by the user but no energy being delivered to the vehicle), comprises 76,698 charging events. Within the data is an ID of the vehicle being charged, the date and time of the beginning and end of the charging event and the battery SoC at the beginning and end of the charging event in twelfths[4]. The charge data were recorded by the car and not the charger; hence, all charge events (including those at work, public destinations and en route) are recorded, minus missing data as discussed below. There are no markers in the data to inform which are carried out at home or otherwise. Due to the emphasis placed on home charging in the project literature [163], the higher likelihood of home-based charging events in the evening where the stress on the network is likely to be greatest and the lack of any information to suggest otherwise, it is assumed in this study that all charge events logged are carried out at home (this is acknowledged as a weakness in using this dataset). Therefore, they are all assumed to take place at a power of 3.7 kW and are applied to the busbar at which that vehicle is instantiated in the study distribution network, in accordance with the charging power available in the MEA project [163, 181].

It is disclosed in the project [163] that there are missing data due to communications and recording equipment failures, and a lack of data storage on the vehicles. It is not

[4]This low level of resolution offered is a result of the EV model used for the trial, and is acknowledged as a limitation to using this approach.

known how much charging data was lost due to these factors[5].

One of the aims of the MEA trial was to investigate how EV charging could be automatically managed to avoid overloading network assets. This was done by employing a concept named in the project documentation as 'Esprit', comprising of a 'monitor controller' installed at the local secondary substation which would monitor the current flow on all three phases, and an 'intelligent control box' installed on the customer's premises, essentially a switch that would disconnect the EV and switch off its charging if the loading conditions at the substation were above a certain threshold. The 'Esprit' system is summarised in Figure 4.6, reproduced from [182].

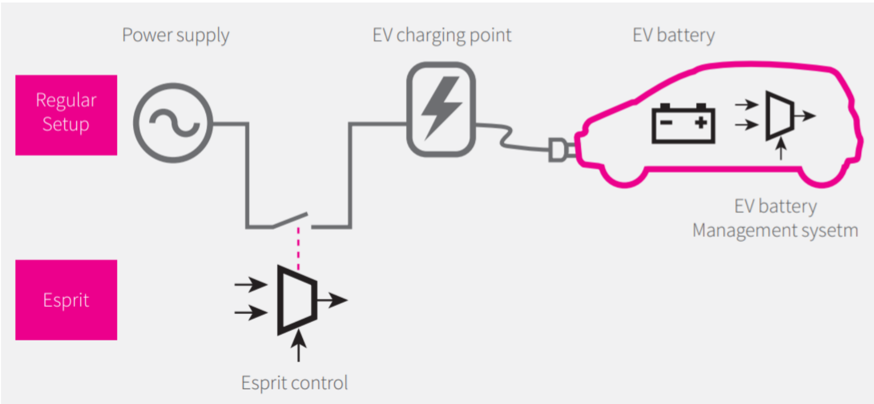

Figure 4.6: Schematic showing 'Esprit' system for management of charging in *My Electric Avenue* trial, source: EA Technology

Data released from the project contains information of the total loading as seen by the monitor controllers and the switch state of each intelligent control box (i.e. when charging was interrupted). However, as each EV is not linked with the substation it is under or the intelligent control box on its charger, it is impossible to quantify how much energy (if any) each car was denied as a result of the 'Esprit' system. Therefore, in the context of this work, this means that the results presented show the effect of an unknown level of managed charging. Clearly, there are improvements that could be made to the completeness of the MEA dataset, and indeed of those of future EV trials. This is expanded on in Section 4.9.

[5]EA Technology, the technical partner of the MEA trial, were contacted for a precise answer on this, but even they are not aware of how much data may be missing from the trial.

4.5.3 Processing the Dataset

Dates of Interest

As stated, the trial was conducted from December 2013 to November 2015. However, the number of trial participants active on each day of the trial did vary; mostly, as expected, that there were less participants active at the very beginning and very end of the trial than during the bulk of the trial. Also, trial participants were seen to be less involved during the periods of Christmas and Easter, likely due to them being on holiday. Figure 4.7 shows the number of active trial participants by day for the duration of the MEA trial.

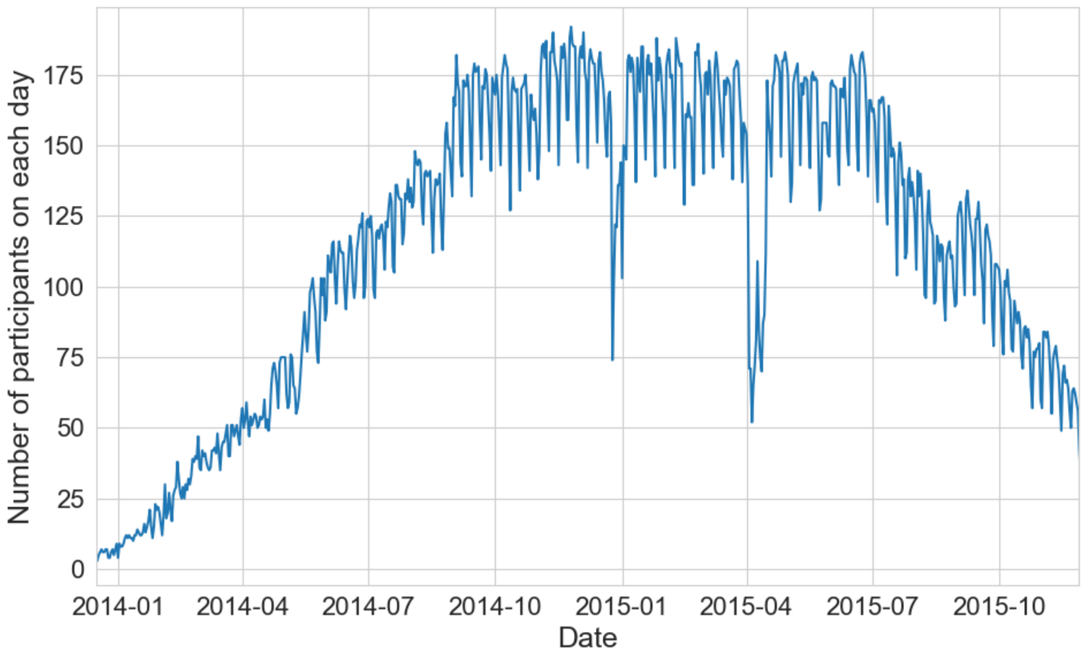

Figure 4.7: Number of active participants per day of *My Electric Avenue* Trial

Based on the result shown in Figure 4.7, the dates for analysis in this work were chosen as 02/08/2014 – 23/12/2014, 02/01/2015 – 28/03/2015 and 14/04/2015 – 02/08/2015 all inclusive. The fluctuating nature of the active participants is due to fewer participants being active on weekend days than weekdays.

Disaggregation of Weekday and Weekend Behaviour

It is often perceived that there is a stark difference in driver behaviour between weekdays and weekend days, mostly due to the presence of commuting on weekdays and a higher occurrence of leisure trips on weekends. To investigate this trend in the MEA dataset, travel diaries (i.e. the series of journeys they took over the course of the trial) for all participants were synthesised from the data. The mean energy usage per participant per day by day of the week for the duration of the dates stated above is shown in Figure 4.8.

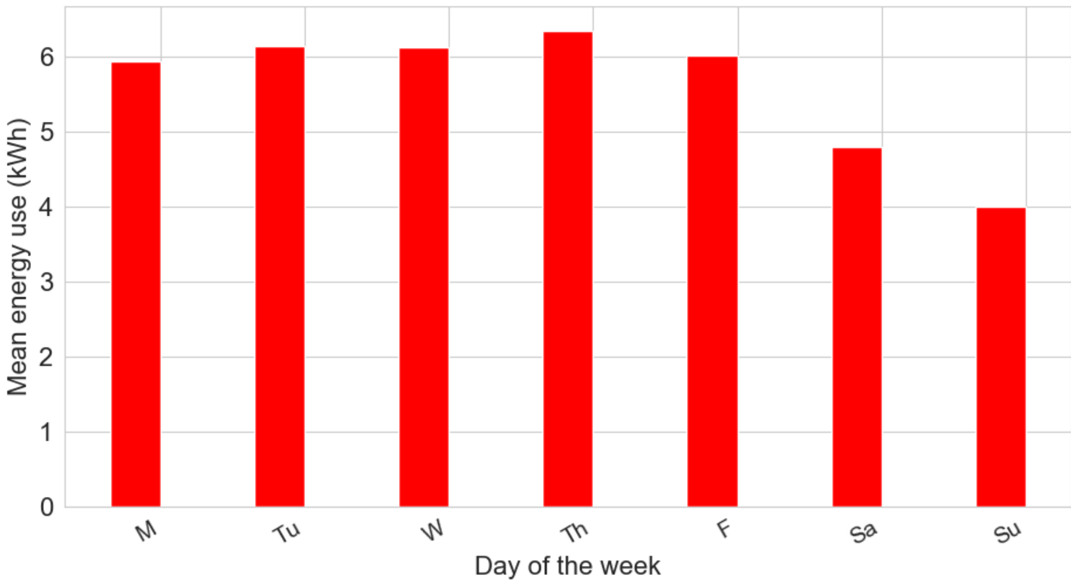

Figure 4.8: Mean energy usage (kWh) per participant per day by day of week during dates of interest of *My Electric Avenue* trial

Figure 4.8 shows that there is a clear distinction between weekday driving behaviour and weekend driving behaviour, in that people tend to travel less on the weekends than they do on weekdays. As a result, charging events were divided into weekday and weekend groups for analysis.

4.5.4 Statistical Analysis of My Electric Avenue Dataset

Trip Data

Figures 4.9 and 4.10 show key patterns in the MEA trip data, as compared to the NTS dataset (as used in Section 4.6). Overall, there are only slight differences in the average travel behaviour of individuals in both sets, though there is significant difference in the variance of the two.

Figure 4.9 shows the variation in trip distance between the NTS dataset and that in the MEA dataset. Though both are dominated by short trips, the average is higher for the NTS dataset. The MEA dataset is constrained by the short range of the vehicles (135 km, according to the EPA real-world ranges [38]) compared to ICVs as used in the NTS dataset.

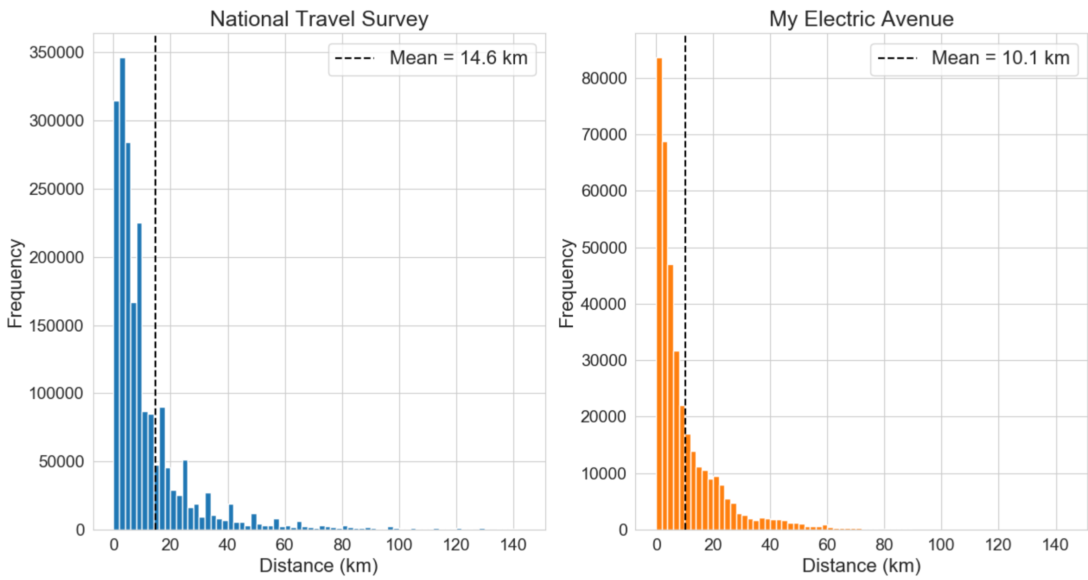

Figure 4.9: Histograms showing distance of journeys taken in UK National Travel Survey (2002-2016) and *My Electric Avenue* trial

Figure 4.10 shows the daily distance per number of vehicles active on that particular day, for both the NTS and the MEA datasets. Remarkably, the mean values are equal to one decimal place (the mean for the NTS is 45.86 km; the mean for MEA is 45.90 km). The skew of the data is notably different: whereas the NTS dataset is dominated by days where the distance is comparatively low (the modal distance was 5-10 km per vehicle), the MEA dataset is skewed to larger distances per day (the modal distances were 45-46 and 49-50 km per vehicle). This could be a consequence of a bias in the study resulting from a self-selecting set of people volunteering to join the trial – who may be more likely to be frequent drivers. However, as before, where there are instances of very large daily distances being completed in the NTS (up to and beyond 200 km per vehicle), there are no daily distances greater than 57 km per vehicle in the MEA dataset – again, due to the range of the vehicle used. The resultant of these two effects is to produce very close means between the two datasets.

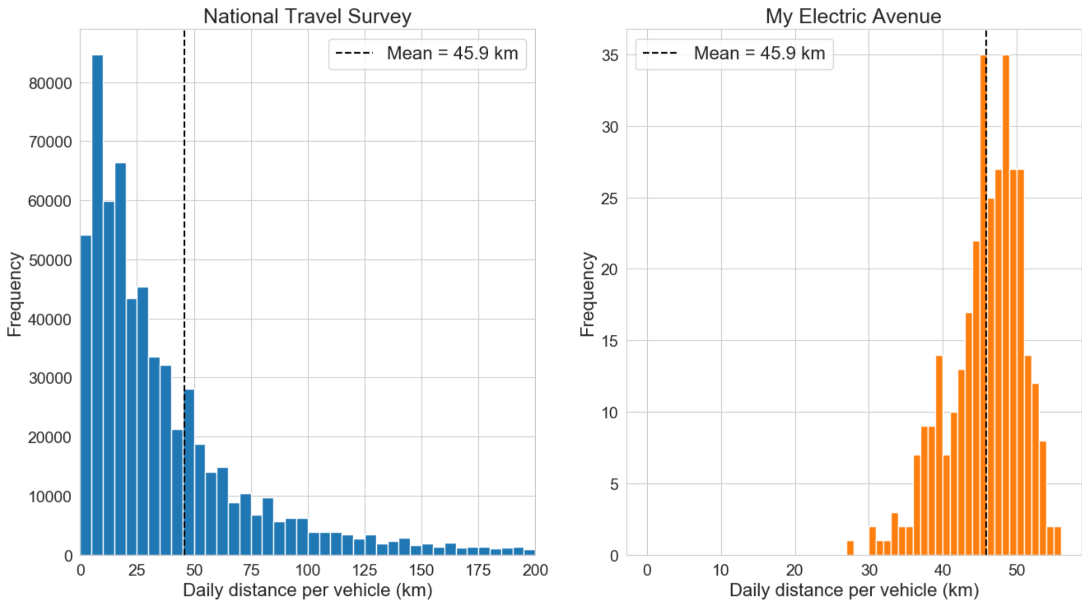

Figure 4.10: Histograms showing daily distance per vehicle for all days in UK National Travel Survey (2002-2016) and *My Electric Avenue* trial

Figure 4.11 shows probability density functions for the arrival times of all journeys in the NTS and MEA trips datasets. As already mentioned, there is no disaggregation of the trip type in the MEA dataset; however, it is assumed that trips that end at home are most likely to be represented by those with arrival times between 16:00-19:00. The afternoon peak is shown to be broadly similar between the two datasets and, although a sharper peak is shown in the NTS data, both plots exhibit a characteristic ‘cat ear’ profile with morning and afternoon peaks.

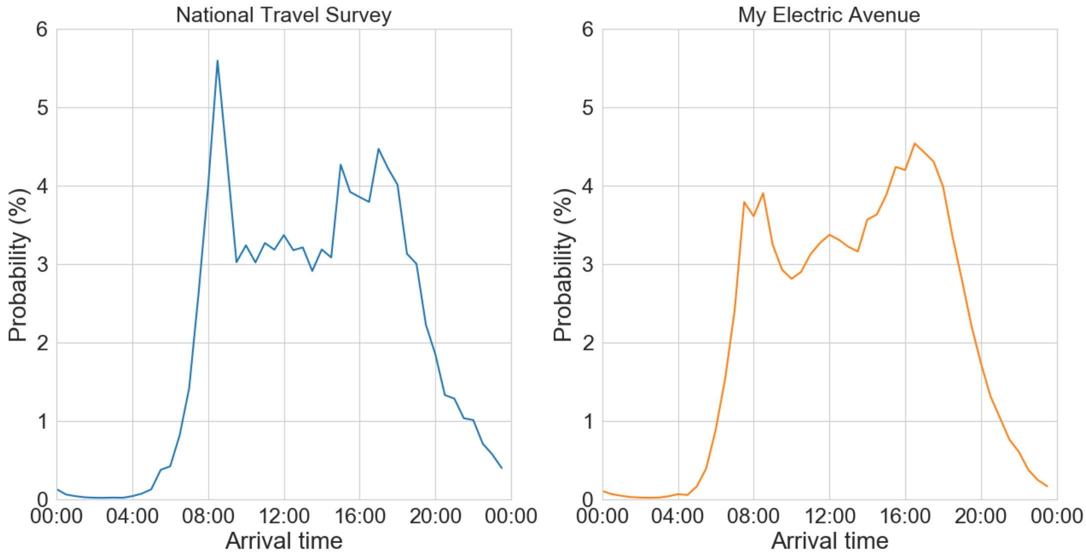

Figure 4.11: Probability density functions of arrival times for all trips in UK National Travel Survey (2002-2016) and *My Electric Avenue* trial

Proportion of Vehicles Charging

Residential EV charging, if uncontrolled, is expected to occur most often in the evening when commuters arrive home from work [136–142, 144–154]. The same trends were observed from the MEA data. Further analysis is presented to examine the temporal variation of charging demand of both weekdays and weekends.

For each day in either the set of weekdays or weekend days during the trial, the total number of active participants was recorded. For each 10 minute period in the day, the number of participants who were charging their vehicle (i.e. had started a charging event and not stopped it) was recorded. The proportion of vehicles charging out of those active on that day was then recorded. Figures 4.12 and 4.13 show density plots of all recorded proportions of vehicles charging for all days during the trial for weekdays and weekend days respectively.

During the trial, the highest proportion of vehicles charging during a 10 minute period was 24.4%, which occurred in the period 18:30-18:40 on a weekday. On average, the peak level of coincidence of vehicles charging is around 15% during the periods 18:30-18:40 and 18:40-18:50 for weekdays and around 14% during the periods 18:20-18:30 and

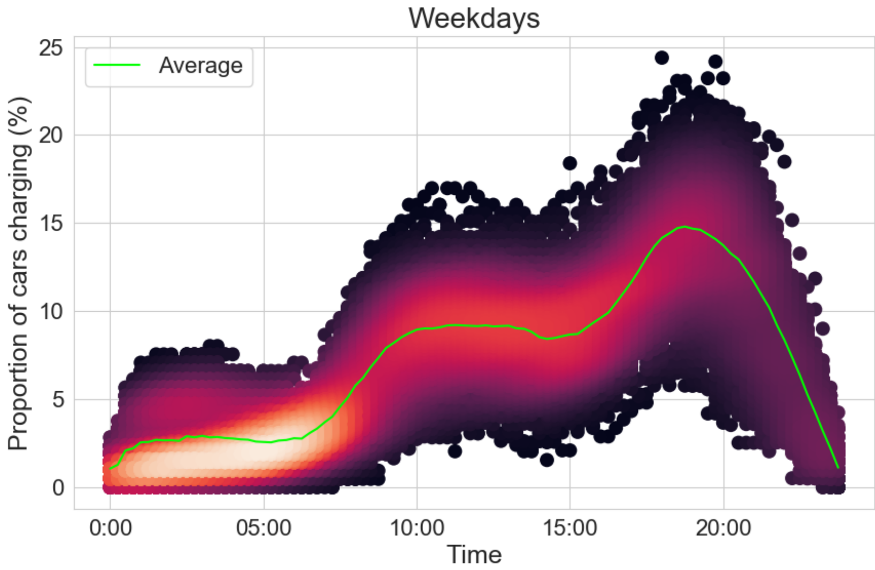

Figure 4.12: Density plot of proportion of vehicles charging in *My Electric Avenue* trial by 10 minute time period - weekdays

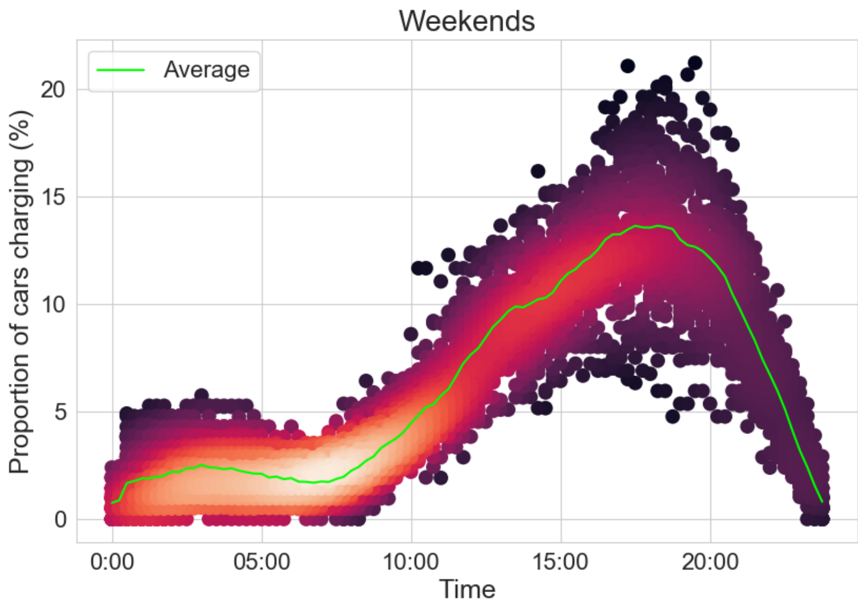

Figure 4.13: Density plot of proportion of vehicles charging in *My Electric Avenue* trial by 10 minute time period - weekends

18:30-18:40 for weekend days.

In [181], Cross and Hartshorn report a diversity factor[6] of ~ 3 for EV charging based on an MC simulation derived from EV trial data. The results shown in Figures 4.12 and 4.13 suggest that perhaps it is somewhat greater, given that at most one in four EVs in the trial was charging simultaneously. However, it is important to recall that the charge events in the MEA dataset are the result of the 'Esprit' charging system (Figure 4.6); therefore, the peak proportion of vehicles charging under an uncontrolled charging scenario could be higher.

Based on the finding that the peak of weekday charging demand was greater than the peak of weekend charging, future analysis presented in this section is based on analysis of weekday charging demand only.

In the simulation (Section 4.5.5), the data presented in Figure 4.12 is assembled into a CDF for each 10 minute period. Examples of such for the period 16:00-19:00 for all weekday charging events in the MEA trial are shown in Figure 4.14.

[6] The diversity factor is the ratio of the sum of the individual non-coincident maximum loads to the maximum demand of the network. It can be thought of as the inverse of the fraction of coincident loads; i.e. here, one in three EVs could be considered to be charging at the same time under peak loading conditions.

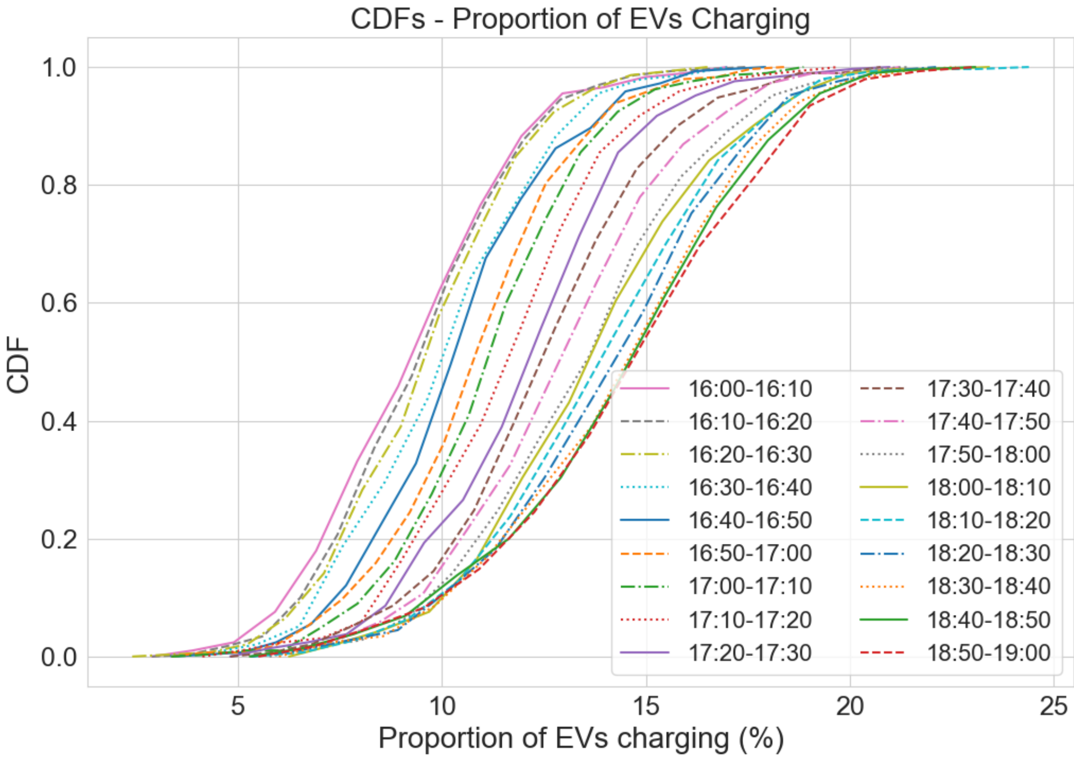

Figure 4.14: Example cumulative distribution functions of proportion of vehicles charging by 10 minute intervals, 16:00-19:00 for all weekday charging events in *My Electric Avenue* trial

Instantaneous Charging Power

As per the analysis in Section 2.2.5, this analysis assumes a lithium-ion charging profile. The profile originally shown in Figure 2.6 is repeated below in Figure 4.15, though C-rate charging power and per unit SoC is replaced with kW charging power and kWh energy storage.

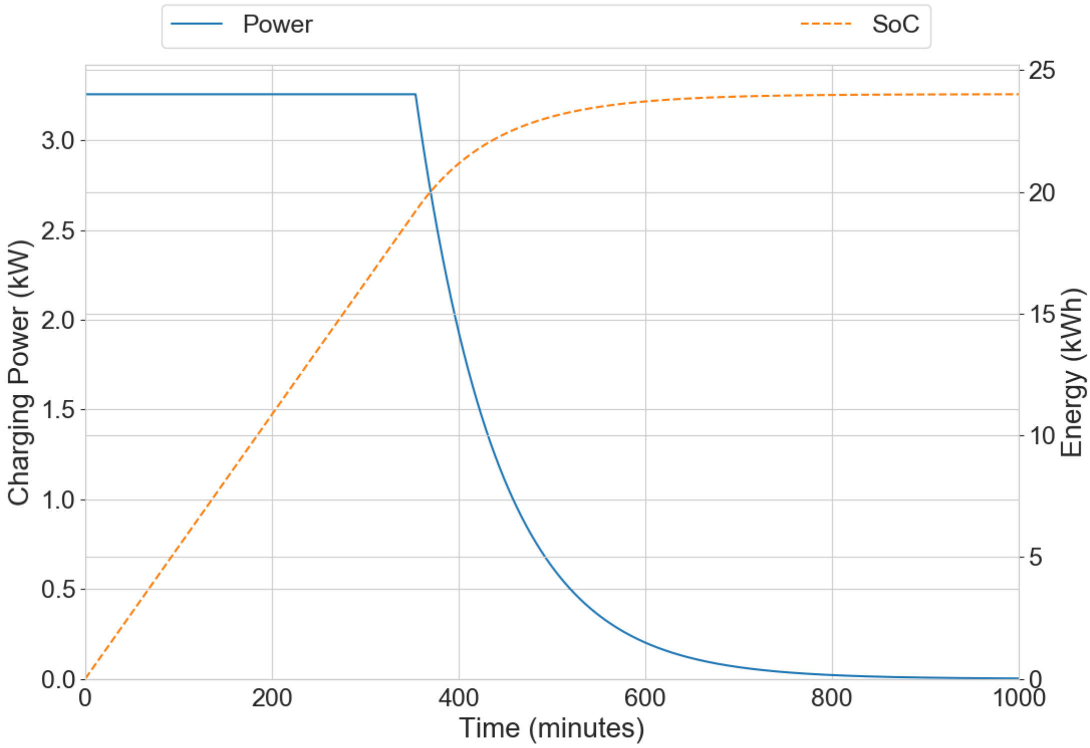

Figure 4.15: Battery charging profile for lithium-ion battery of capacity 24 kWh at charging power of 3.7 kW

Recall that the charging power (kW) that an EV can draw during charge event e $P_e(t)$ is related to the time t relative to the time the vehicle starts charging via (4.1).

$$P_e(t) = \begin{cases} P_e^{DC}, & t \leq t_e^{\gamma} \\ P_e^{DC} e^{-\lambda_e (t - t_e^{\gamma})}, & t > t_e^{\gamma} \end{cases} \tag{4.1}$$

where, as before, P_e^{DC} is the maximum rated DC charging power available during charge event e, λ_e is the CV region decay constant during charge event e and t^{γ} is the time at which the EV's SoC reached γ, at which point the charging transitions from the CC to the CV region. As before, $\gamma = 0.8$ in accordance with results presented in [84].

P_e^{DC} is equal to the AC power 3.7 kW in accordance with charging power available during the MEA project [163,181] multiplied by an AC/DC conversion efficiency of 0.88 in common with analysis in Chapter 2 – originally taken from analysis in [83].

Similarly to analysis presented in Section 2.2.5, the time at which the battery's SoC

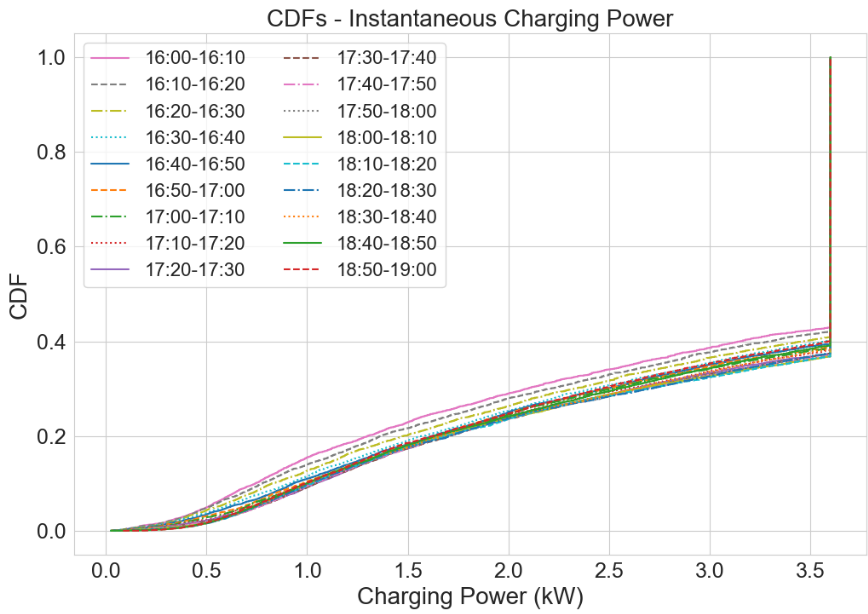

Figure 4.16: Example cumulative distribution functions of instantaneous charging power by 10 minute intervals, 16:00-19:00 for all weekday charging events in *My Electric Avenue* trial

reaches γ is found as in (4.2).

$$t_e^{\gamma} = \frac{(\gamma - S_e^s)C_e}{P_e^{DC}} + t_e^s \tag{4.2}$$

where S_e^s is the SoC of the EV upon plugin (in twelfths) in charge event e, t_e^s is the plug-in time and C_e is the battery capacity of the EV during charge event e – for the MEA analysis, this is fixed at 24 kWh.

For a proportion of time that an EV was charging during the trial, it will have been within the CV region of the charging profile and hence the power it was drawing from the charger would have been less than the maximum rated DC charging power. For each charging event, given S_e^s and t_e^s, t_e^{γ} is calculated. Then, $P_e(t)$ is calculated according to (4.1). Figure 4.16 shows example CDFs of the instantaneous charging power $P_e(t)$ by 10 minute time period from 16:00-19:00 for all weekday charging events in the MEA trial.

The time periods shown in Figure 4.16 are shown because they align with when the highest number of vehicles are being plugged in. At this time, approximately 60% of vehicles plugged in are charging at full power in the CC region of Figure 4.15 and the remainder are at various stages in the CV region.

4.5.5 Simulation

Overview

For each timestep, the CDF governing the proportion of cars charging at that period based on all days in the trial (which is equivalent to a 'slice' of the data in Figure 4.12) is returned and sampled from. Following the establishment of the proportion of cars charging, this is applied to the network by generating a random number for each vehicle established in the network from Algorithm 1. At this point, each car is then either charging or not charging. If it is charging, its instantaneous charging power is sampled from a CDF governing the instantaneous charging power of all cars plugged in during that time period on all days in the trial (e.g. Figure 4.16). The corresponding charging power is then applied to the relevant busbar with which this vehicle is associated.

The process used is shown in Figure 4.17.

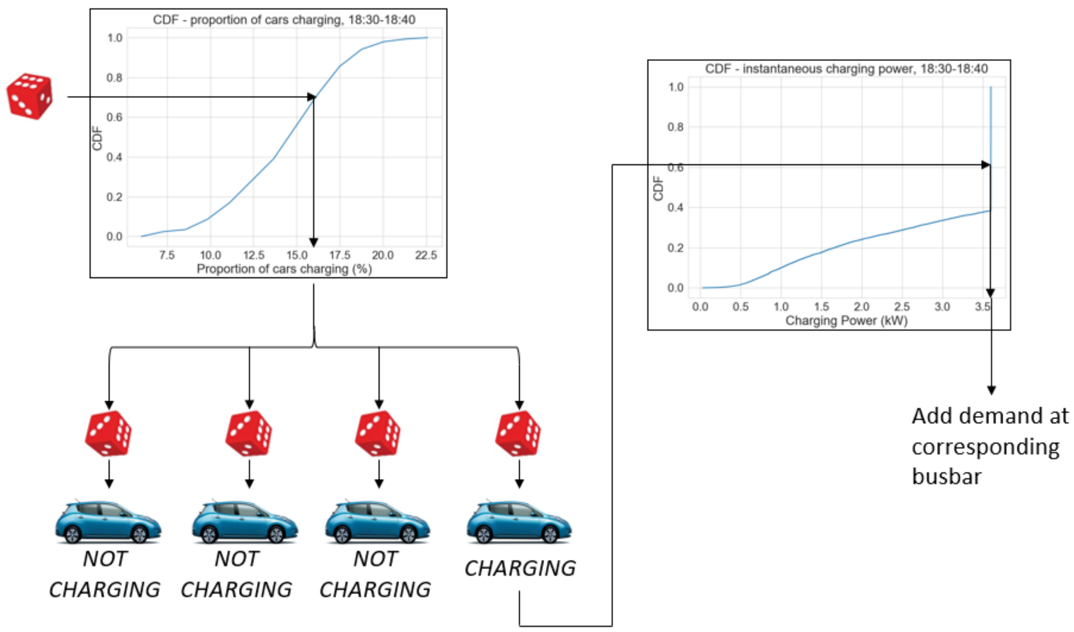

Figure 4.17: Process used for simulation of EV charging impact on distribution network using charging data from *My Electric Avenue* trial

Algorithm 2 expands on the concepts illustrated in Figure 4.17; the steps taken are shown for each trial. Each trial was carried out 100 times to give a low variation in output results; the spread of results is shown in Section 4.5.6.

Algorithm 2 Applying EV charging loads from *My Electric Avenue* dataset on distribution network model

for each time period (1-144) **do**
    Sample from CDF (e.g. Figure 4.14)
    Return proportion of EVs charging p_{EV}
    for each household in the network **do**
        Return domestic demand ▷ from domestic demand model (Section 4.4)
        Apply domestic demand at corresponding busbar in network
    for each vehicle in the network **do**
        Return random number $0 \leq r_2 \leq 1$
        if $r_2 \leq p_{EV}$: **then**
            Sample from CDF (e.g. Figure 4.16)
            Return vehicle charging power
            Apply charging power as demand at corresponding busbar in network
    Run load flow, save results

The EV charging power is assigned with a power factor of 0.98 (lagging), in accordance with previous analysis of the MEA project [183]. The domestic load assigned to nodes is applied at a power factor of 0.95 (lagging) in accordance with the approach used in [184].

4.5.6 Results

Overall Network Loading

Figure 4.18 shows a 24-hour plot of the total loading (domestic plus EV charging) to the Pollokshields network with the analysis detailed in Algorithm 2 run in 10 minute timesteps. The spread of MC results is shown in Figure 4.18: each shaded region represents the spread of 95% of the MC simulation results, with the mean result shown in a solid line for each colour.

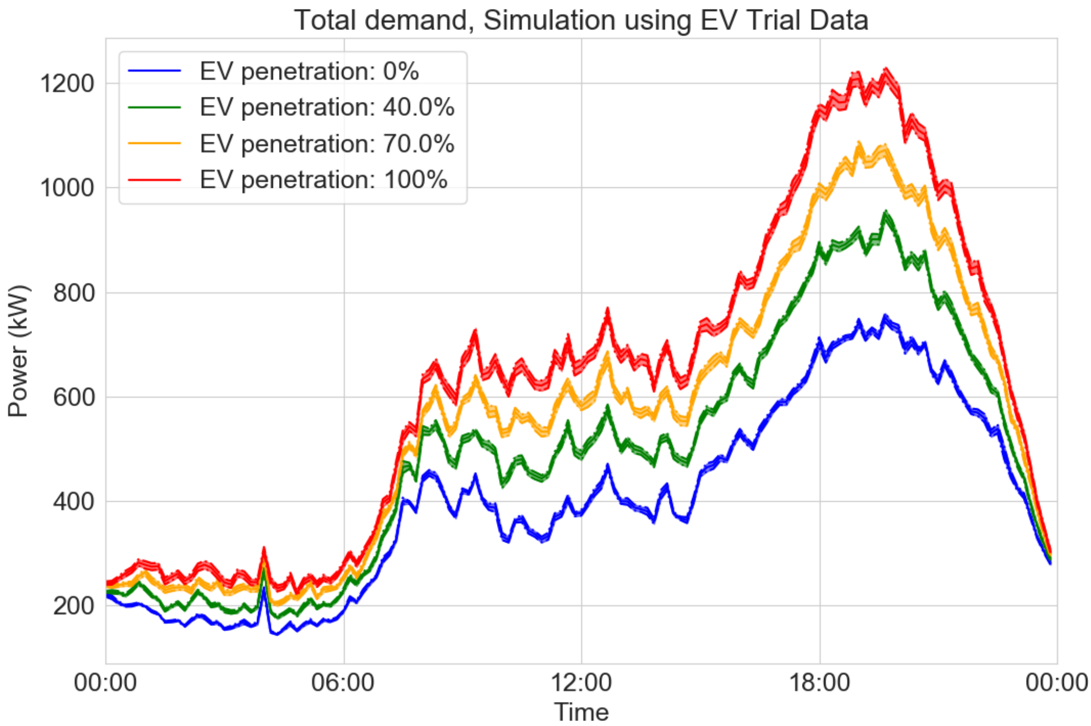

Figure 4.18: Overall network loading of Pollokshields network resulting from simulation using *My Electric Avenue* trial data

Figure 4.18 suggests that if various proportions of vehicles in the Pollokshields study network area were replaced by EVs, and their charging behaviour were similar to that displayed in the MEA EV trial including any curtailment from the 'Esprit' system, then a significant increase in demand to the network could be seen: from a 0% to 100% EV uptake, the network peak demand increases by 58% from 763 kW to 1206 kW. Figure 4.18 also shows that the most problematic area is shown to be in the evening between 15:00-21:00. This was expected from analysis of charging behaviour (Figure 4.12) and the domestic demand model used (Figure 4.5). In the following sections, the impact on the network is investigated by examining the likely loading of transformers and lines and the likely voltage drops at customer endpoints, given the set of real network data.

Loading on Secondary Transformers

There are five secondary transformers in the Pollokshields study distribution network, numbered 1-5 in Figure 4.19.

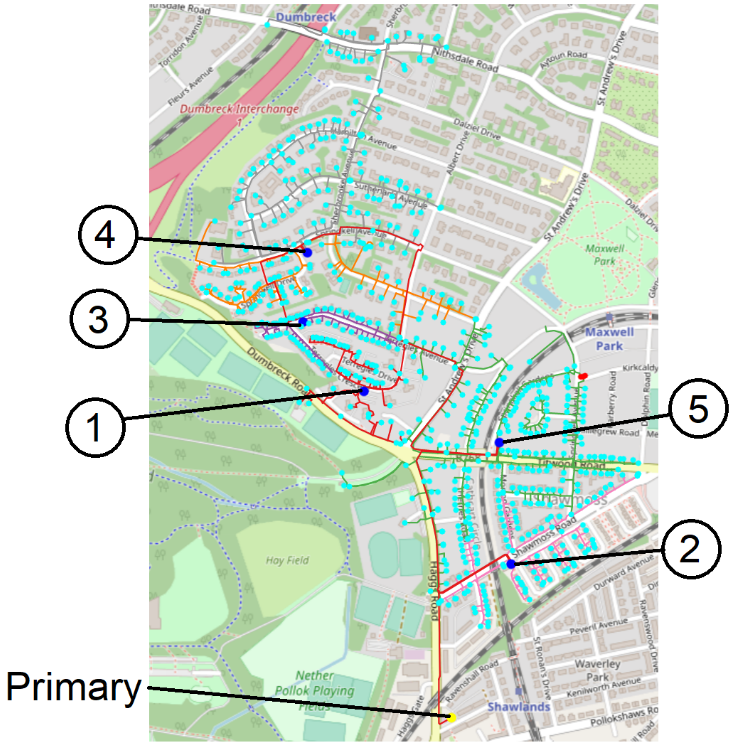

Figure 4.19: Pollokshields network plotted over OpenStreetMap data showing location of 5 secondary transformers

Figure 4.20 shows the expected peak loading for all 5 secondary transformers for different levels of EV penetration. In Figure 4.20, vertical error bars show the range of the 95% confidence interval for each peak loading result.

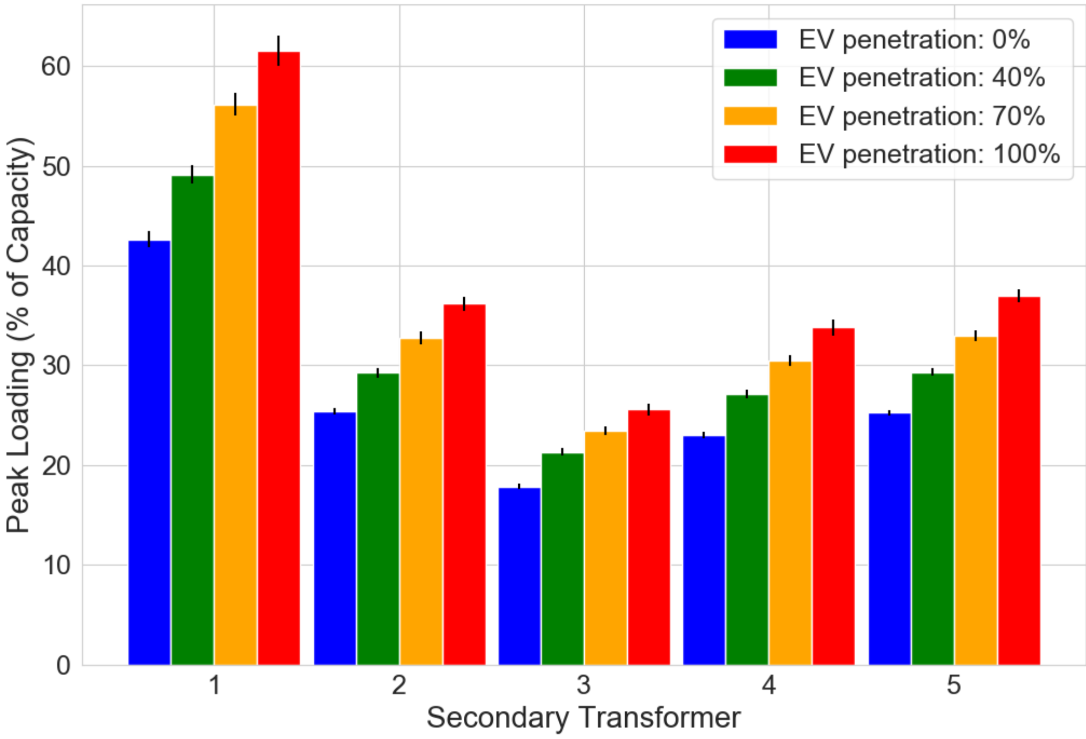

Figure 4.20: Peak loading (% capacity) on secondary transformers due to EV charging load at different levels of EV penetration

Figure 4.20 shows that although every transformer is expected to see a peak load increase from an increasing penetration of EVs, some transformers see a more significant increase than others. Transformer 3 is expected to see its peak increase from 18% under 0% EV penetration to 28% under 100% EV penetration; far less than transformer 1, which is expected to see its peak loading increase from 41% to 68% for the same levels of EV penetration.

It is shown in both Figures 4.18 and 4.20 that although the spread of MC trial results increases as more EVs are simulated, it remains low with the difference between a confidence limit and the mean never exceeding 2.5% of the mean. This is due to the significant amount of 'averaging' that occurs as part of the simulation as it simulates a large number of individual loads.

The presence of EVs in the network is shown to have a significant effect on the demand seen by transformer 1. If all vehicles in this network were replaced by EVs who

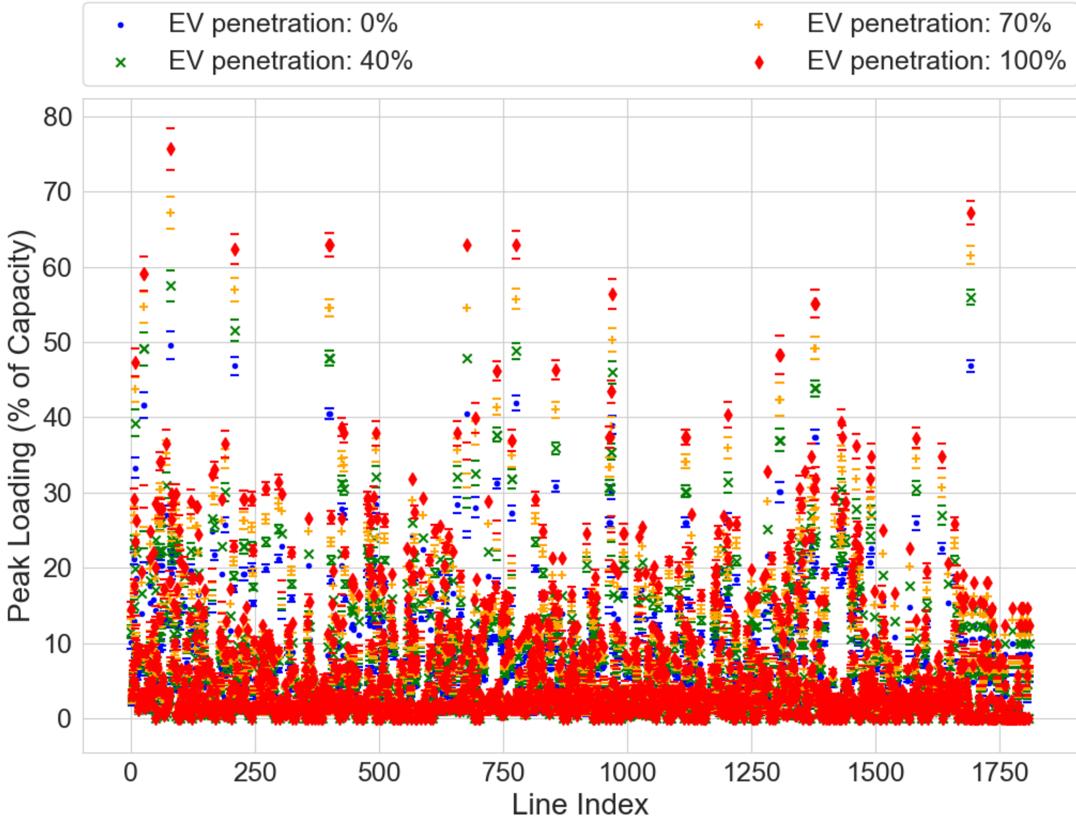

Figure 4.21: Increased loading (% capacity) on all lines due to EV charging load at different levels of EV penetration, simulation using *My Electric Avenue* data

follow similar uncontrolled charging behaviour as that exemplified in the MEA trial, then it is shown to be likely that the peak load on this transformer will exceed 50% of its thermal capacity.

Line Loading

There are 1840 lines (of which 150 are 11 kV circuits and 1690 are 0.4 kV circuits) in the study network. Figure 4.21 shows the mean result for all simulations of the peak loading on all lines as a percentage of their capacity for different levels of EV uptake. Horizontal lines are shown either size of each marker to represent the 95% confidence interval of results.

As with the secondary transformers, some assets are shown to face a significantly greater loading increase than others. While the heaviest loaded line before EV uptake

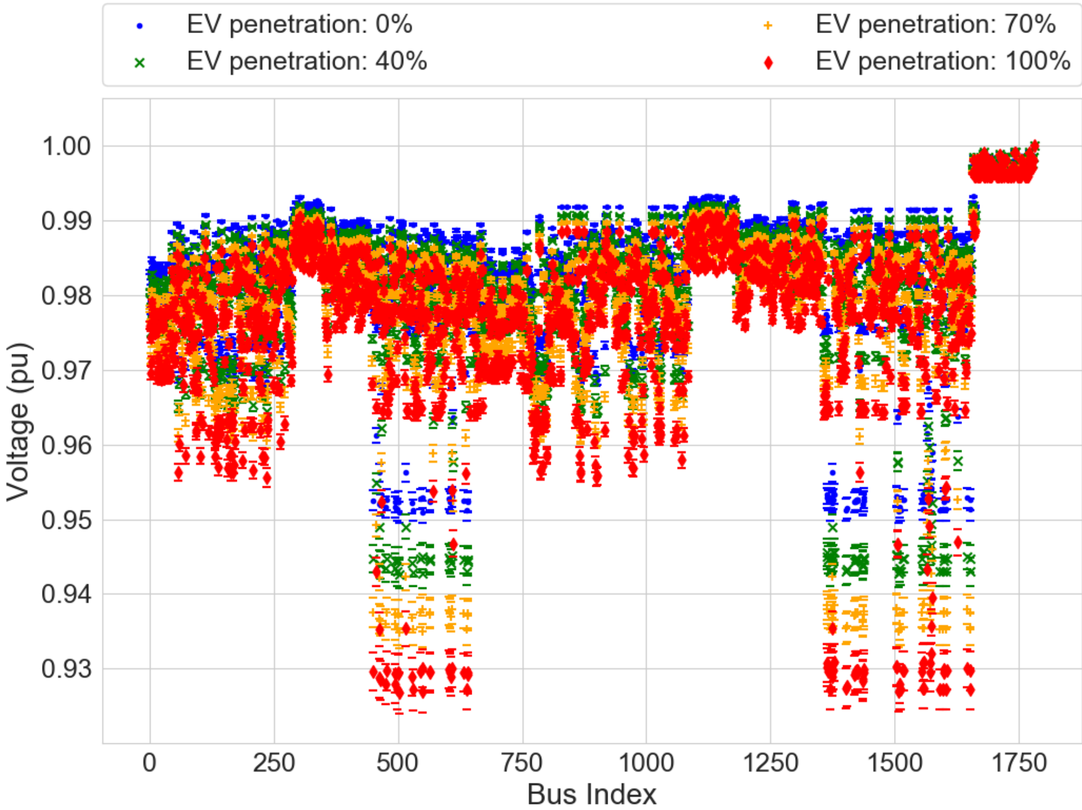

Figure 4.22: Minimum voltage at endpoints due to EV charging load at different levels of EV penetration, simulation using *My Electric Avenue* data

is expected to be loaded at 48% of its capacity, the same line is brought to above 80% of its capacity when 100% of vehicles in the network area are replaced by EVs.

Endpoint Voltage Drop

The impact of EV uptake on the per unit (pu) voltage at the endpoints of the network is shown in Figure 4.22. As previously stated, the primary transformer is able to change its tap setting to attempt to maintain an LV bus voltage of 1 pu, whereas secondary transformers are fixed at a tap setting of 0%.

Table 4.1 shows a series of summary metrics on the violation of voltage levels in the simulation using the MEA dataset, in terms of i) the proportion of time for which the limits were violated, ii) the minimum voltage that was found and iii) the average breach magnitude. All values in Table 4.1 are reported as mean values of the 100 trials conducted.

Table 4.1: Summary metrics for violation of voltage limits in Pollokshields network following simulation of EV charging impact using *My Electric Avenue* data

EV penetration (%)	**0**	**40**	**70**	**100**
Proportion of time voltages in violation (%)	–	1.38	14.51	21.84
Minimum voltage (pu)	0.950	0.938	0.930	0.924
Average breach magnitude (pu)	–	0.0005	0.0095	0.01453

Voltage limits in the GB system at the customer endpoint are +10%/-6% [185]. As shown in Figure 4.22 and Table 4.1, the voltages at multiple endpoints are below 0.94 pu (and therefore outwith the allowable limits) for at least some of the time for EV penetrations of 40% and over. The deviation from the limits for 40% EV penetration is very slight: the average minimum endpoint voltage over 100 trials was 0.938 pu, and on average the voltage was outwith limits for 1.4% of the time.

Options available to the DNO for regulating these voltages include setting the target voltage of the LV bus of the primary substation higher than 1 pu, or to adjust the tap settings on the secondary transformers while offline. However, the presence of any generation whose output was not coincident with EV charging demand (e.g. rooftop solar PV, whose output would be very low in winter evenings when the EV/domestic demand would be at its highest, and at its greatest in the middle of summer days where the EV charging load is less) could render this approach unsuitable as a voltage rise in the middle of the day could take the endpoint voltage out of allowable limits. Therefore, further studies would need to be undertaken to establish the possible extent of voltage rise in the network before these changes could be made.

A potentially easier and lower-cost solution to enable the whole GB system to facilitate a greater penetration of EVs for a given cost of reinforcement could be to simply relax the voltage constraints themselves, given that it has been shown that this results in very limited effects on device performance. This is further discussed in Section 5.7.1.

4.5.7 Discussion

Statistical analysis of EV charging data from the MEA trial has shown that EV charging appears to be fairly diverse: in over 12 months of data, the greatest concurrence of vehicles charging at the same time occurred at under 25% of vehicles, and on average the peak coincidence of charging vehicles was under 15% of vehicles. These values, however, are after a regime of demand side management in which the charging of EVs is curtailed during peak times if conditions on local substations demand it. Given that the EV demand peak occurs at around the same time as the existing domestic demand network peak, the network is expected to undergo some stress if it was to accommodate uncontrolled EV charging, which would likely necessitate costly upgrades. Most of the issues shown begin to breach either network limits of DNO planners' rules of thumb after 40-70% of vehicles in the network are replaced by EVs.

The analysis presented could be used in a planning context to help direct the investments of DNOs, thus enabling a lower cost of the integration of EVs within the power system. Specifically, results such as those presented in Figures 4.21 and 4.22 could be used to assess whether voltage deviations or thermal loading (or both) are driving any need for reinforcement, and at which locations in the network these would appear first.

As previously discussed in Section 4.2.1, while the use of EV trial data in EV charging modelling has its merits, it fixes the results of analysis to a particular set of technologies (namely the battery capacity, charger power and level of access to charging) that were available during the trial and to the particular set of individuals who took part in the trial. As a difference in travel behaviour can be expected between populations of different socioeconomic makeup, a limitation of the use of EV trial data exists here. In the next section, similar analysis will be conducted using travel survey data, which although requires the simulation of charging events, is suggested to hold distinct advantages.

4.6 Simulation of Charging Schedules given Travel Survey Data

4.6.1 Introduction

Motivation

As discussed previously in Section 4.2.1, EV trial data is generally tied to a particular set of technologies and individuals that made up the trial in question: for instance, in the MEA trial used for the analysis in Section 4.5, all EVs whose charging events were recorded had battery capacities of 24 kWh and home charging power ratings of 3.7 kW [163]. As these parameters are likely to change as the EV sector evolves, it is suggested that charging behaviour is likely to change with it. For example, a vehicle with a battery of 100 kWh capacity could be expected to charge on fewer occasions than one with a capacity of 24 kWh as it would be able to travel a greater distance before running out of range. By using travel data such as that available from the NTS dataset, charging schedules can be established based on the data for a variety of different EV parameters to examine the likely differences in charging behaviour and hence network demand when these parameters change. Furthermore, this can eliminate any bias that may result from self-selecting subsets of individuals volunteering to take part in EV trials, who might be expected to tend towards certain kinds of travel behaviour and are therefore less likely to be representative of typical vehicle users.

Charging Behaviour Models

The governing assumption used when inferring charging schedules from travel data is that individuals' travel habits will remain constant whether they are using an EV or an ICV[7]. Furthermore, the assumptions made regarding how individuals will behave will have an effect on the resulting network demand. To mitigate this uncertainty, two methods of developing charging schedules based on the travel data in the NTS dataset are presented:

[7]This assumption has enormous implications for the role of EVs within the future transport and wider energy system. It is further discussed in the Epilogue.

1. An **idealised** method, in which charging schedules are derived in the same way as presented in Section 2.2.4, except for two modifications. Firstly, in Chapter 2, the initial SoC was set to 80%, so as to provide a fair basis for the evaluation of the vehicles' charging time penalties. In this chapter, the analysis focuses on the resulting demand on the electricity network from charging and hence the assumption of initial SoC has a significant effect on the frequency of the necessitated charge events. To reflect the idea that these travel diaries represent a week in the life of an EV driver which could be at any time, the initial SoC in this chapter is randomised for each travel diary in the interval $\{S^{min}, 1\}$, where S^{min} is the minimum allowable SoC – refer to equation (2.4). Secondly, whereas in Chapter 2 the EV was to finish its travel diary with an SoC equal to that which it started with, in this chapter the vehicle does not have to replenish its expended energy and can finish on any SoC, so long as it is above the prescribed minimum. This is to avoid a clump of charging activity at the end of the week which would result otherwise.

2. A **routine** charging method, in which charging schedules are derived in an identical manner to that of the idealised charging method above, except that $\Pi_k = 1$ for all k (refer to equation (2.3)) corresponding to trips ending at home – in other words, drivers will always plug in when they arrive at home irrespective of their SoC. This is done to reflect a set of behaviours where either plugging in upon arrival at home is of minimal inconvenience such that it becomes routine, or where drivers are incentivised to plug their vehicles in whenever they are home. This may become more likely with the advent of V2G technology, in which drivers can be remunerated for making their cars available overnight for the provision of grid services such as frequency response.

The relative merits and drawbacks of these methods for deriving charging schedules based on NTS data are discussed in Section 4.6.5.

4.6.2 UK National Travel Survey Data

In Chapter 2, every travel diary in the NTS dataset was analysed and as such, a subset of five years (2012-2016 inclusive) was selected due to the high computational cost of the analysis carried out. In this chapter, individual travel diaries are selected from the dataset and applied to vehicles, according to their likely socioeconomic properties as explained in Section 4.3.4. Therefore, the complete fifteen year dataset (2002-2016) is used for this chapter.

The full 2002-2016 dataset contains details of 2,042,058 trips between 126,186 unique vehicle-based travel diaries. The method by which the trip data and individual data were cross-referenced to generate unique week-long travel diaries is the same as that described in Section 2.2.1.

Figure 4.23 shows the variation in trip distance (km) and time (minutes) of all car-based trips between years. The mean distance varies only within the range 14.36-15.33 km (2010 and 2007 respectively) and the mean time varies within the range 20.89-22.81 minutes (2002 and 2015 respectively). Although the variation within each year is significant, the variation between years is evidenced to be very slight.

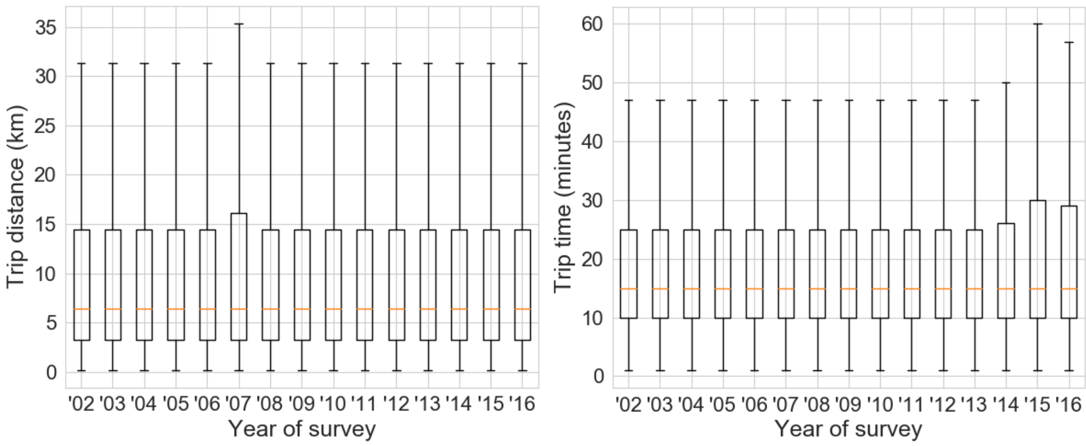

Figure 4.23: Boxplots showing variation in trip distance (km) and duration (minutes) across 15 years (2002-2016) of UK National Travel Survey data (outliers omitted for clarity)

Example NTS Travel Diary

An example of the resulting seven-day travel diaries is shown in Table 4.2. This individual reported being employed during the week of the survey, and that they generally take the bus to work. However, as can be seen in Table 4.2, the individual does report one return trip to work using a car on the Sunday (perhaps due to a reduced bus timetable).

Table 4.2: Example UK National Travel Survey travel diary (car-based trips)

Trip #	Origin	Destination	Trip Start	Trip End	Distance (miles)
1	Home	Food shop	Tu 09:30	Tu 09:50	3
2	Food shop	Home	Tu 10:40	Tu 11:00	3
3	Home	Other escort	Tu 18:15	Tu 18:20	0.25
4	Other escort	Home	Tu 18:20	Tu 18:25	0.25
5	Home	Other escort	Tu 19:40	Tu 19:45	0.25
6	Other escort	Home	Tu 19:50	Tu 19:55	0.25
7	Home	Food shop	W 09:30	W 09:50	3
8	Food shop	Home	W 10:30	W 10:45	3
9	Home	Work	Su 07:40	Su 08:00	7
10	Work	Home	Su 17:00	Su 17:20	7

Example Idealised Charging Schedule

Table 4.3 shows the derived charging schedule using the idealised charging methods for the set of trips in Table 4.2. E^s and E^d denote the energy storage of the EV's battery at the start and end of the charge event respectively (equal to the SoC multiplied by the battery capacity).

Table 4.3: Idealised charging schedule derived from NTS travel diary in Table 4.2 for an EV with a battery capacity of 24 kWh and a home charger rated at 3.7 kW AC, 88% efficiency

Trip #	Charge Type	Plug-in	Plug-out	E^s (kWh)	E^d (kWh)	P^{DC} (kW)
8	home	W 10:45	Su 07:40	8.44	24	3.26

Table 4.3 shows that the EV was able to charge sufficiently to meet the energy requirements of its travel diary with one parked charging event taken at home at the end of trip 8. Note that although the EV could have charged after trips 2, 4 and 6, the driver chose not to as they could defer their charging until later in the week.

Example Routine Charging Schedule

Table 4.4 shows a schedule of charge events produced using the routine charging method for the NTS travel diary in Table 4.2.

Table 4.4: Routine charging schedule derived from NTS travel diary in Table 4.2 for an EV with a battery capacity of 24 kWh and a home charger rated at 3.7 kW AC, 88% efficiency

Trip #	**Charge Type**	**Plug-in**	**Plug-out**	E^s **(kWh)**	E^d **(kWh)**	P^{DC} **(kW)**
2	home	Tu 11:00	Tu 18:15	10.36	24	3.26
4	home	Tu 18:25	Tu 19:40	23.86	24	3.26
6	home	Tu 19:55	W 09:30	23.86	24	3.26
8	home	W 10:45	Su 07:40	22.36	24	3.26

In Table 4.4, the EV charges at all the home-based opportunities it gets: in this example, whereas it did not charge after trips 4, 6 and 8 under the idealised scenario, it did charge after these trips in the routine scenario. As a result, its energy requirements for these charge events tends to be less. Given that the total charging time is dictated by the duration of the parking event, charging under the routine method of charge event scheduling is typically more flexible than charging under the idealised method.

Number of NTS Travel Diaries by Economic Activity and Means of Travel to Work

The economic activity (employed, self-employed or unemployed in the week during which the data was collected) and the means of travel to work (train, bus, car driver, car passenger, bicycle, on foot or 'did not answer' (DNA)) were collected from the individual assigned to each vehicle, and that pair of characteristics was then assigned to each travel diary. Table 4.5 shows the number of NTS travel diaries within each category of economic activity and means of travel to work.

The vast majority (84.7%) of individuals who completed NTS travel diaries were in employment during the week of the survey, 11.6% were reportedly self-employed and the remaining 3.7% were unemployed. The latter all answered DNA when asked their means of travel to work. Of the other economic activity types, there is shown to be an

Table 4.5: Number of UK National Travel Survey (2002-2016) travel diaries by economic activity and means of travel to work category

	Train	**Bus**	**Car driver**	**Car passenger**	**Bicycle**	**On foot**	**DNA**
Employed	2,444	967	46,158	734	1,234	2,989	32,806
Self-employed	261	69	6,413	96	72	564	6,766
Unemployed	0	0	0	0	0	0	2,346

uneven spread of travel diaries between categories of means of travel to work, with car driver being by far the most reported: 54.4% of those in employment drove a car to work and 45.9% of those self-employed reported the same.

As shown in Table 4.5, there are some combinations of economic activity and means of travel to work that contain very few or zero travel diaries. Whereas in the Census questionnaire a number of individuals who responded 'unemployed' also gave a means of travel to work, the NTS individual questionnaire has any unemployed individual as 'DNA' in means of travel to work. Therefore, if any vehicle is returned as being associated with an individual who is unemployed (or economically inactive), it is assigned an unemployed/DNA travel diary. Furthermore, no travel diary can be assigned more than once in the same network, so as to avoid duplicate charge events. As such, when a travel diary is assigned, it is removed from the set of travel diaries in that combination of economic activity and means of travel to work that can be assigned in the future. If this set is reduced to empty, a travel diary from the 'DNA' field of the corresponding economic activity is assigned.

Total Distance Covered and Time Taken of NTS Travel Diaries by Employment and Means of Travel to Work

Figures 4.24 and 4.25 show CDFs for the total distance driven (km) and total driving time (minutes) respectively for the NTS diaries by economic activity and means of travel to work (Table 4.5). Recall that while an individual might travel to work by some means other than driving, they are linked to a vehicle in the NTS data that they use for other purposes.

Figure 4.24: Cumulative distribution functions showing probability of travel diary exceeding given total distance (km) by economic activity and means of travel to work

Figure 4.25: Cumulative distribution functions showing probability of travel diary exceeding given total driving time (minutes) by economic activity and means of travel to work

As shown in Figures 4.24 and 4.25, while there is not a significant difference in the total distance or time driven by varying economic activity types, there does appear to be a difference by means of travel to work, with the car driver and car passenger classifications significantly more likely to drive further than those who take other means of transport to work. For example, whereas the median distance driven by all employed respondents who did not take a car to work is approximately 100 km, the median distance driven by those who did take a car to work as a driver is over 200 km.

Parking Event Arrival Time in NTS Travel Diaries by Employment and Means of Travel to Work

Figures 4.26-4.28 show probability distribution functions (PDFs) for the journey end time – and hence parking event arrival time – for all trip data from the NTS travel diaries ending at home, work and public destinations respectively, by economic activity and means of travel to work for weekday trips in 15 minute intervals. Note that only trips that started on weekdays are included, in line with the general assumption that EV charging peak is to be more severe on weekdays than weekends [135, 181].

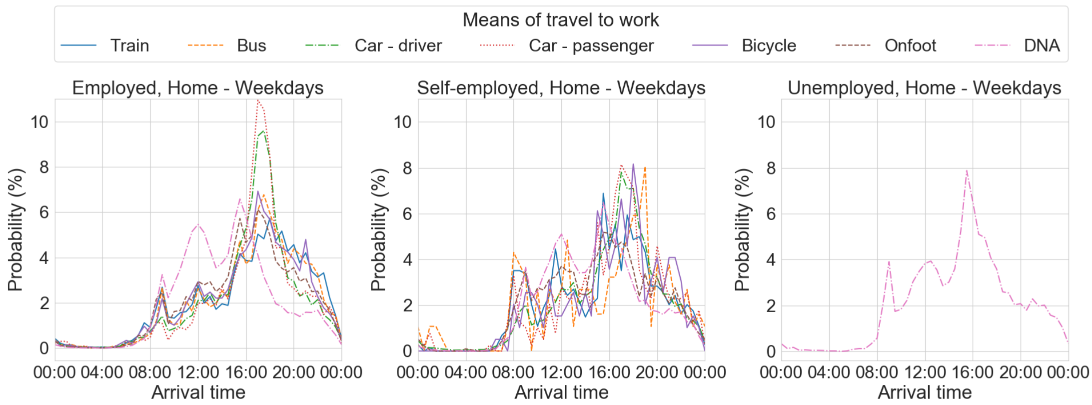

Figure 4.26: Probability density functions showing probability of home parking event arrival time by economic activity and means of travel to work – weekday trips

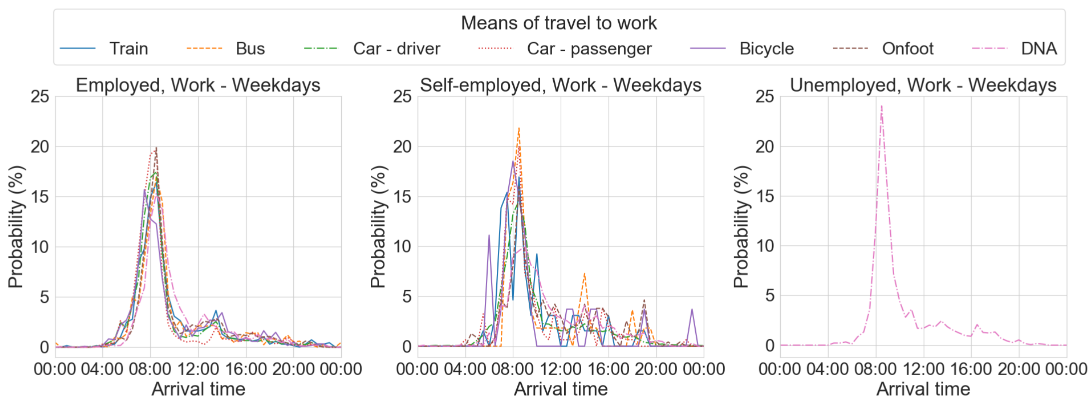

Figure 4.27: Probability density functions showing probability of work parking event arrival time by economic activity and means of travel to work – weekday trips

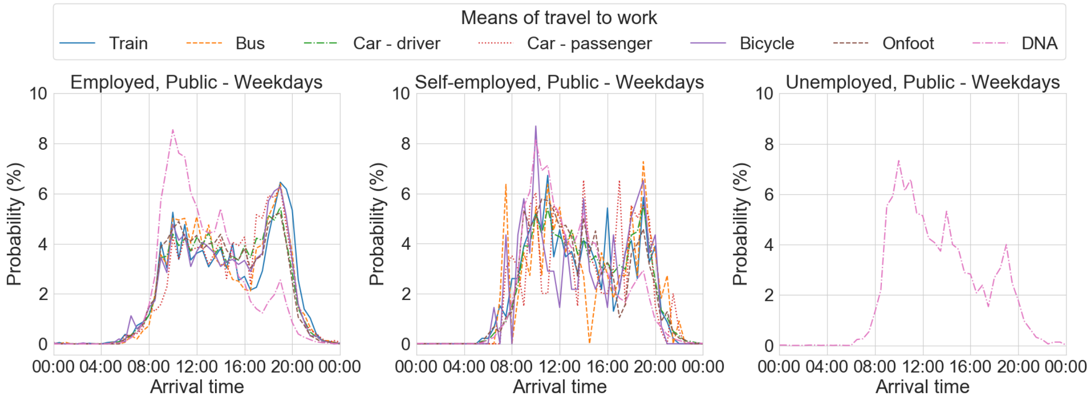

Figure 4.28: Probability density functions showing probability of public destination parking event arrival time by economic activity and means of travel to work – weekday trips

Figure 4.26 shows characteristic spikes in arrival time in the evening around 17:00-19:00 as drivers arrive home from work; this behaviour is shown to be particularly apparent for employed individuals who use a car to get to work, either as driver or passenger. The self-employed dataset shows a less pronounced peak, but the highest values remain within 17:00-19:00. Individuals reporting themselves as unemployed exhibit broadly similar behaviour to the other categories, though the peak in their arrival time at home is earlier than employed or self-employed individuals, in this case happening before 16:00.

Arrival times at work (Figure 4.27) are shown to be significantly more concentrated than arrival times at home, with the majority of arrival times occurring within the bounds of 07:30-09:00, with no significant difference to report between different economic activities and means of travel to work. A noteworthy and unexpected result is the presence of arrival times at work of unemployed individuals. It is expected that in line with the fact that these individuals report not attending work during the week of the survey, the destinations of these journeys are ‘education’, which are included within the set of ‘work’ destinations as discussed (Section 2.3).

The arrival times at public destinations (Figure 4.28) are shown to differ as a result of economic activity and means of travel to work. Whereas employed individuals, aside from those who did not answer the question regarding means of travel to work, are more likely to visit public destinations in the evening, self-employed and unemployed individuals are more likely to visit them in the late morning/early afternoon.

Parking Event Duration in NTS Travel Diaries by Employment and Means of Travel to Work

Figures 4.29- 4.31 show CDFs for the parking event duration for all trip data from the NTS travel diaries by economic activity and means of travel to work for weekday trips in 15 minute intervals.

Figure 4.29: Cumulative distribution functions of parking event duration of trips ending at home within UK National Travel Survey travel diaries by economic activity and means of travel to work – weekday trips

Figure 4.30: Cumulative distribution functions of parking event duration of trips ending at work within UK National Travel Survey travel diaries by economic activity and means of travel to work – weekday trips

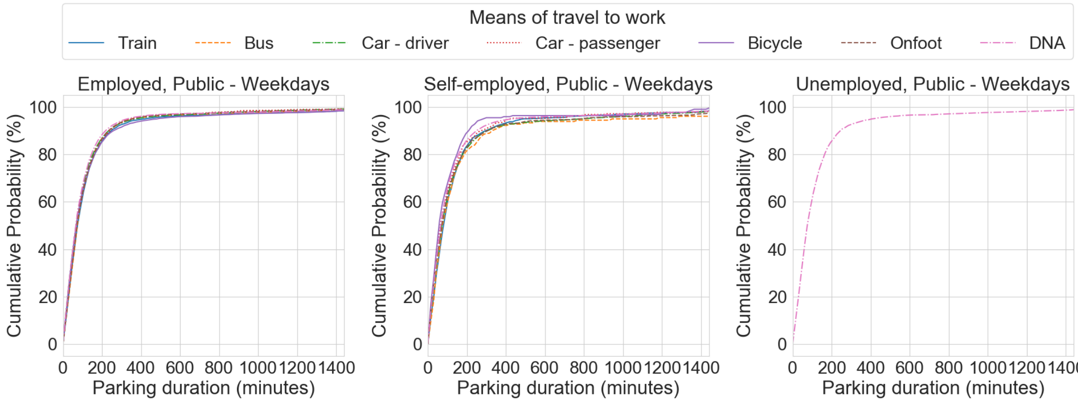

Figure 4.31: Cumulative distribution functions of parking event duration of trips ending at public destinations within UK National Travel Survey travel diaries by economic activity and means of travel to work – weekday trips

Figure 4.29 shows that individuals across all types of economic activity and means of travel to work are prone to long parking sessions at home, with 70-80% of parking events at least 200 minutes in duration. For most groups of individuals, there is approximately a 20% likelihood that their parking event will be longer than a full 24 hour period. The 'S'-shaped curve characteristic of all three charts shows that there is a cluster of parking events that are shorter in duration (0-400 minutes) and another cluster around 800-1000 minutes, which is particularly accentuated for the employed individuals who use a car to get to work either as a driver or passenger. This is thought to align with typical overnight parking events between arriving at home from work one day and driving to work again the next.

Figure 4.30 shows that for all combinations of economic activity and means of travel to work, a large proportion of individuals are likely to spend between 400 and 600 minutes parked at a workplace, which is thought to be reflective of a typical duration of a working day. Both employed and self-employed individuals who travel to work on foot or did not answer the means to work question are less likely to stay for a longer duration, with 40-60% of these individuals likely to stay for 300 minutes or less. The unemployed group display similar characteristics to the others. As before, this is suggested to be due to journeys with an 'education' purpose, which are typically of a similar duration to stays at work.

Figure 4.31 shows that parking events at public destinations are considerably shorted than those at home or work. There is shown to be no significant difference based on economic activity or means of travel to work, with around 90% of all groups parking for less than 250 minutes.

In both sets of figures (4.26-4.28 and 4.29-4.31) the self-employed distributions are shown to be 'spikier' with greater variations between adjacent points. This is due to the greater variation in these populations, which are smaller than others as shown in Table 4.5.

4.6.3 Assignment of EV Parameters

Whereas the analysis based on the MEA EV trial presented in Section 4.5 was constrained to the simulation of EVs with 24 kWh batteries, 3.7 kW charging and access to charging at home only, a key advantage of the analysis presented in this section is that these parameters can be changed. The EV parameters that can be changed are the same as analysed in Chapter 2: battery capacity, charger power and level of access to charging at different locations.

In Section 4.6.4, results are presented using a 'base case' of 24 kWh, with access to the low power charging scenario for home charging only, to allow direct comparison with the study using MEA data (Section 4.5). In Section 4.7, EV parameters are assigned probabilistically to represent a future scenario in which there is variety in the models of EVs driven and the type and power rating of the charging they can access. In Section 4.8, all EVs in the network are given the same parameters, which are changed to investigate the effect of these parameters on the resulting demand and effect on the distribution network.

4.6.4 Comparison to using EV Trial Data

Base Case for Comparison with *My Electric Avenue* Study

To provide a comparison between the results of the study using the MEA trial data (Section 4.6) and of the study using NTS data in this section, the latter was run for both idealised and routine methods for the Pollokshields study network for a 'base case' in which all EVs in the area had 24 kWh batteries and access to charging at home only under the low power scenario (and therefore 3.7 kW at-home charging). Although the battery capacity and charger power were straightforward to quantify, the level of access to charging was not. The participants in MEA did have access to charging at other locations, but there is no labelling of charge events. Due to the focus on residential charging during the trial and the generally low uptake of workplace and public charging infrastructure at the time of the trial, it is proposed that this configuration best represents the use case in the MEA trial.

All results presented below are for the charging demand arising from the second and third days of the NTS travel diaries (i.e. Tuesday-Wednesday), thus minimising the boundary effects caused by the influence of the initial SoC assumption. While the application of a randomised initial SoC was earlier justified, there could conceivably be a non-uniform distribution: given that all travel diaries are synthesised such that they begin on Monday, it could be reasonable that SoCs would tend to be higher, as drivers may have had more opportunity to charge on Sunday – which typically has a smaller driving energy requirement (see Figure 4.8)). It is recommended that the effect of the assumption regarding the initial SoC on the resulting EV charging demand profiles be investigated by a sensitivity study.

As for the simulation using MEA data (Section 4.5), EV charging loads are applied to the network with a power factor of 0.98 as per [183] and domestic loads are applied with a power factor of 0.95 as per [184].

In this section, 10 trials were conducted for each penetration level and method of deriving charging schedules from travel data. These are much fewer than those in the simulation using EV trial data due to the comparatively computationally expensive nature of the simulation. As shown, there is only a slight variation in results due to a significant diversification effect as a result of simulating up to 1,000 vehicles on each trial, each with individual travel diaries. Accordingly, the 95% confidence interval as shown in Figure 4.32 deviates a maximum of 4.8% away from the mean.

Results

The loading of the entire Pollokshields study network is shown for the idealised and routine charging schedules in Figure 4.32 for all levels of EV penetration trialled in the study. Figure 4.33 shows the percentage loading of all secondary transformers in the Pollokshields network, Figure 4.34 shows a scatter diagram of percentage loading of every line in the network and Figure 4.35 shows the per unit voltage at customer endpoints in the network.

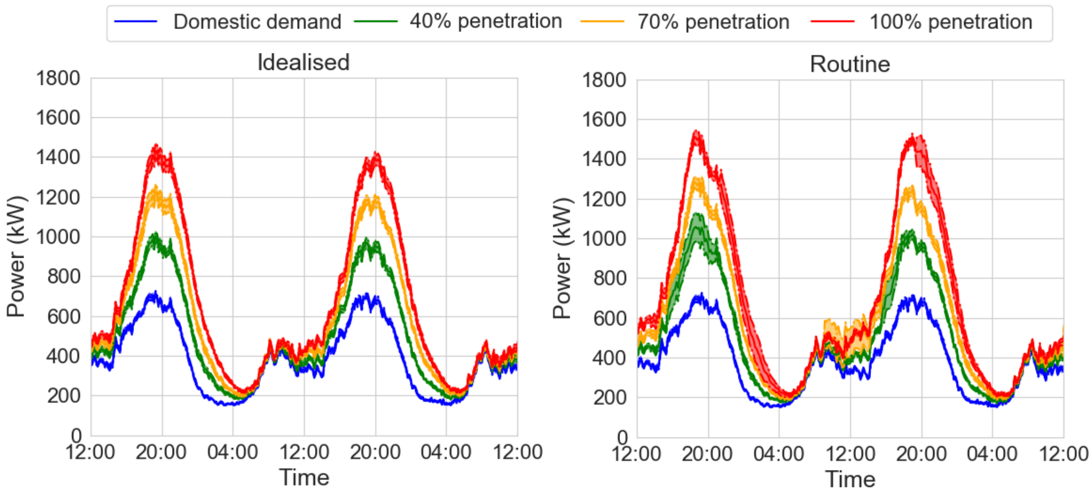

Figure 4.32: Loading of Pollokshields network for varying penetrations of EVs and different methods of deriving charging schedules, 'base case' (all EVs 24 kWh batteries, low power charging scenario and H¬W¬P charging access)

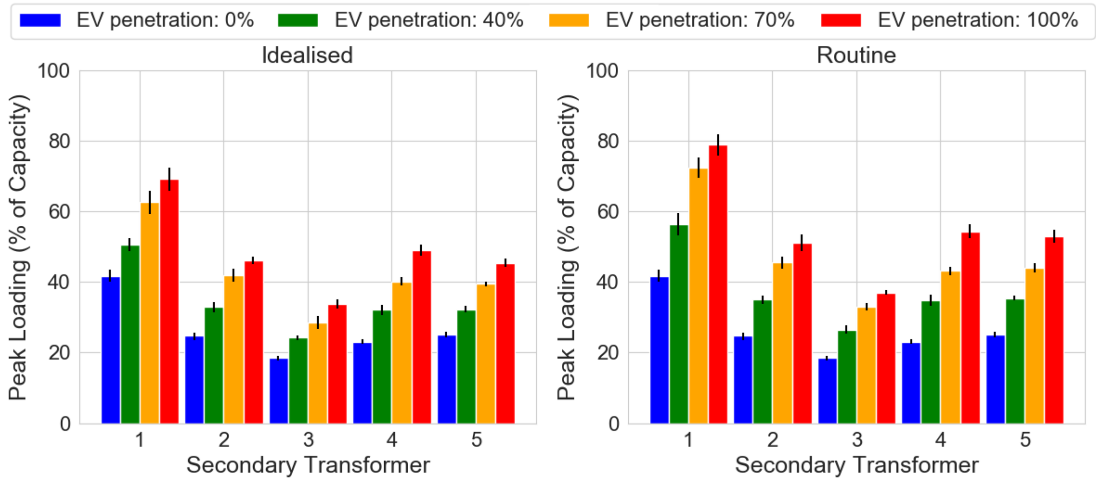

Figure 4.33: Loading of secondary transformers 1-5 in Pollokshields network for varying penetrations of EVs and different methods of deriving charging schedules, 'base case' (all EVs 24 kWh batteries, low power charging scenario and H¬W¬P charging access)

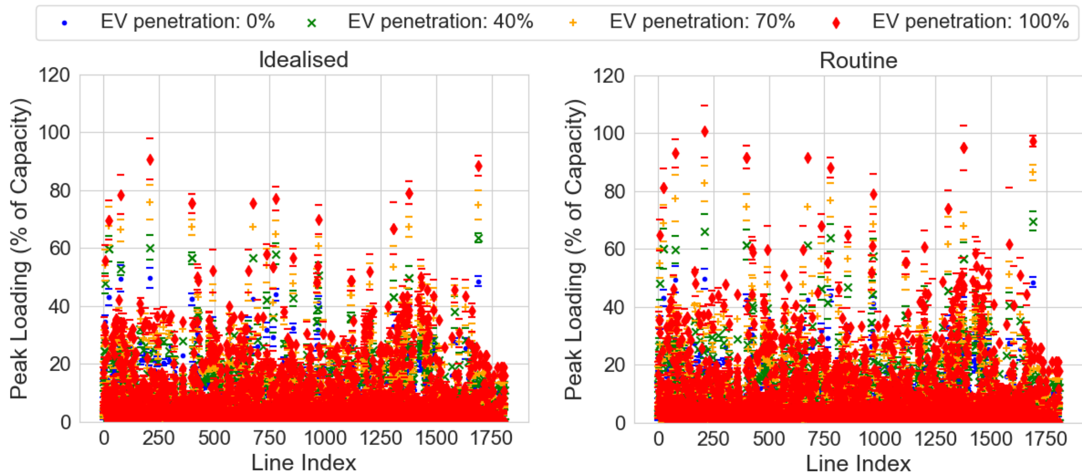

Figure 4.34: Peak loading of lines in Pollokshields network for varying penetrations of EVs and different methods of deriving charging schedules, 'base case' (all EVs 24 kWh batteries, low power charging scenario and H¬W¬P charging access)

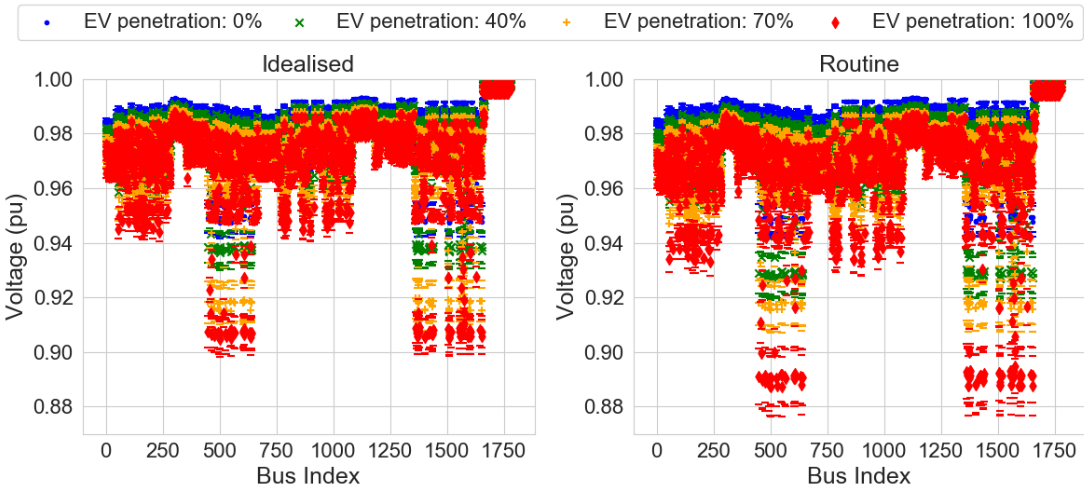

Figure 4.35: Minimum endpoint voltages in Pollokshields network for varying penetrations of EVs and different methods of deriving charging schedules, 'base case' (all EVs 24 kWh batteries, low power charging scenario and H¬W¬P charging access)

As for the analysis using the MEA dataset, table 4.6 shows a series of summary metrics on the violation of voltage levels in the simulation using derived charge schedules from NTS travel diaries for both idealised and routine schedules, again in terms of i) the proportion of time for which the limits were violated, ii) the minimum voltage that was found and iii) the average breach magnitude. All values in Table 4.6 are reported as mean values of the 10 trials conducted.

Table 4.6: Summary metrics for violation of voltage limits in Pollokshields network following simulation of EV charging impact using derived charging schedules from UK National Travel Survey travel diaries

		IDEALISED			ROUTINE		
EV penetration (%)	**0**	**40**	**70**	**100**	**40**	**70**	**100**
Proportion of time voltages in violation (%)	–	4.17	20.83	31.94	18.06	24.31	32.64
Minimum voltage (pu)	0.950	0.929	0.908	0.899	0.917	0.901	0.877
Average breach magnitude (pu)	–	0.0084	0.0098	0.0150	0.0102	0.0092	0.0170

Figure 4.32-4.35 show a dramatic increase in the peak loading of the network follow-

ing the introduction of EVs for all methods of modelling individuals' charging behaviour, with at least a doubling of total peak demand (Figure 4.32) expected for 100% penetration of EVs. The peak loads in the routine case is shown to be slightly greater ($\sim$ 7%) than those in the idealised case. However, the significant effect of EV parameters (particularly battery capacity) on the charging behaviour of individuals under the idealised case means that the difference is starker for different sets of parameters. This is explored further in Section 4.8.

The pattern of charging demand displayed in the simulation using NTS travel data is shown to be remarkably similar to that using MEA charge data in terms of the temporal variation in demand, with the peak of EV charging demand occurring within the time period 18:00-20:00. The magnitude of the peak is around 15-25% higher when NTS travel data was used, depending on the modelling behaviour used. Subsequently, the impact of EV charging on the network is shown to be more severe when modelling using NTS data, by numerical comparison of the results in Tables 4.1 and 4.6. The difference can be accounted for by the consideration of three factors. Firstly, due to the demand side management system employed, a proportion of charge events in the MEA trial were interrupted at peak time. Hence, whereas the results presented in Section 4.5.6 actually show the impact of controlled charging, the results presented in this section show the impact of uncontrolled charging. Secondly, the base case of home charging access only does not allow for workplace or public charging, of which there is likely to be an amount in the MEA dataset: this means that EVs under the NTS 'base case' will have to rely on residential charging to a greater extent than those in the MEA simulation. Thirdly, as already mentioned there is an unknown amount of missing charge event data in the MEA charging dataset. For these reasons, it is suggested that using both methods to derive charging schedules from NTS data, representing the possible spread in charging demand, is a more reliable method of characterising network impact from EV charging.

4.6.5 Comparison of Methods Used to Derive Charging Schedules from UK National Travel Survey Data for the 'Base Case' Parameters

Results

Figure 4.36 shows the total demand on the Pollokshields network from 100% penetration for EVs for both methods of deriving charging schedules from travel data, offering a comparison between the 100% traces in Figure 4.32.

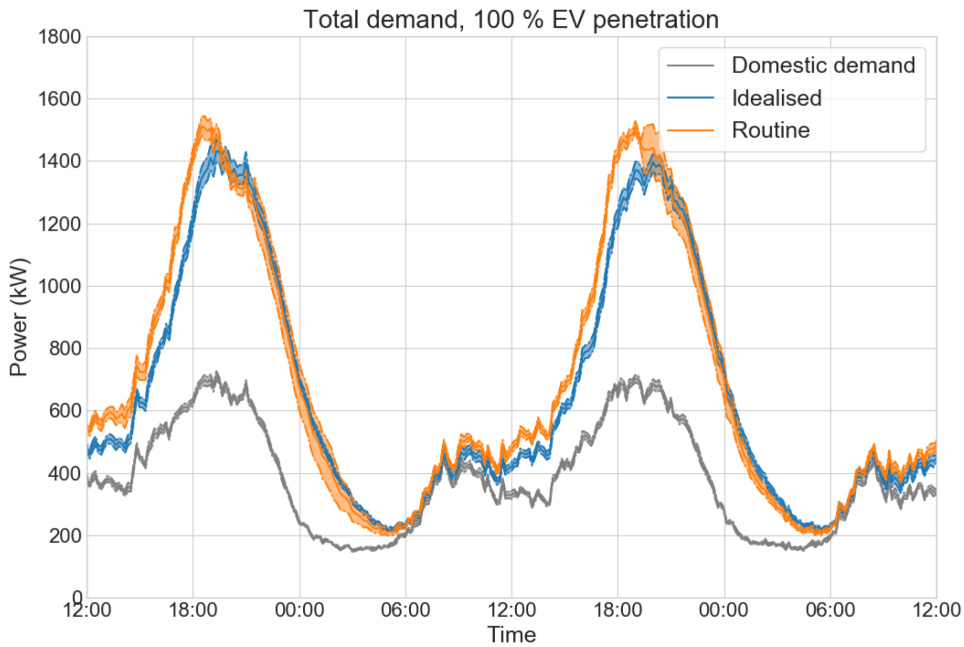

Figure 4.36: Comparison of methods used to derive charging schedules – loading of Pollokshields network for 100% penetration of EVs, 'base case' (all EVs 24 kWh batteries, low power charging scenario and H¬W¬P charging access)

For the base case EV parameters, both methods show a similar level of total demand. As could be expected, the routine charging model gives the highest peak demand – though the difference is not great. This is because while vehicles are plugging in every time they arrive home, their energy requirement upon plugin tends to be smaller as a result of the increased charging frequency.

The patterns seen in Figure 4.36 are explained in Figure 4.37, which shows the proportion of EVs in the network charging (left) and the proportion of EVs in the network charging at full power, in the CC region of the lithium-ion battery charging curve assumed (right).

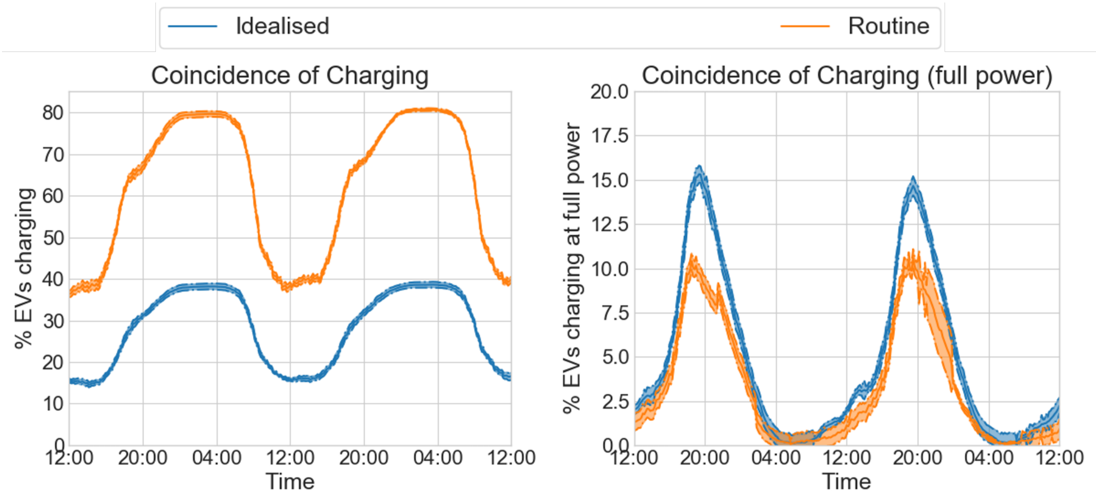

Figure 4.37: Comparison of methods used to derive charging schedules – proportion of EVs charging (left) and proportion of EVs charging at full power (right) in Pollokshields network for 100% penetration of EVs, 'base case' (all EVs 24 kWh batteries, low power charging scenario and H¬W¬P charging access)

In the routine charging schedule, all EVs that are parked at home overnight (around 80% of those in the network) are charging. Note that this does not include those that are plugged in but not actively charging because they are already at 100% SoC. In the idealised charging schedule, around half of that proportion of cars is charging at any given time, peaking at just under 40% of cars in the network.

The routine charging schedule is shown to have fewer EVs charging at full power during peak time: this is because due to their increased frequency of plugin, they are more likely to start charging with a higher SoC (having charged more recently than if using the idealised method) and hence they will leave the CC region of the charging profile sooner. The idealised charging schedule has a greater proportion of EVs charging at full power during peak time, which also could be expected: as these vehicles are seeking the fewest possible charging opportunities, they are more likely to begin charging events with a lower SoC and hence be charging at full power for longer.

Note that because the vehicle does not have to return to the same SoC as it started the week with, the total energy transferred (i.e. the area under each curve) does not have to be equal between cases. Figure 4.38 shows the total energy added to all vehicles in the Pollokshields network for 100% EV penetration, by the different methods of deriving charging schedules from the NTS travel diaries. The height of the bars show the mean value across all trials, and the error bars show the spread of results within the 95% confidence interval.

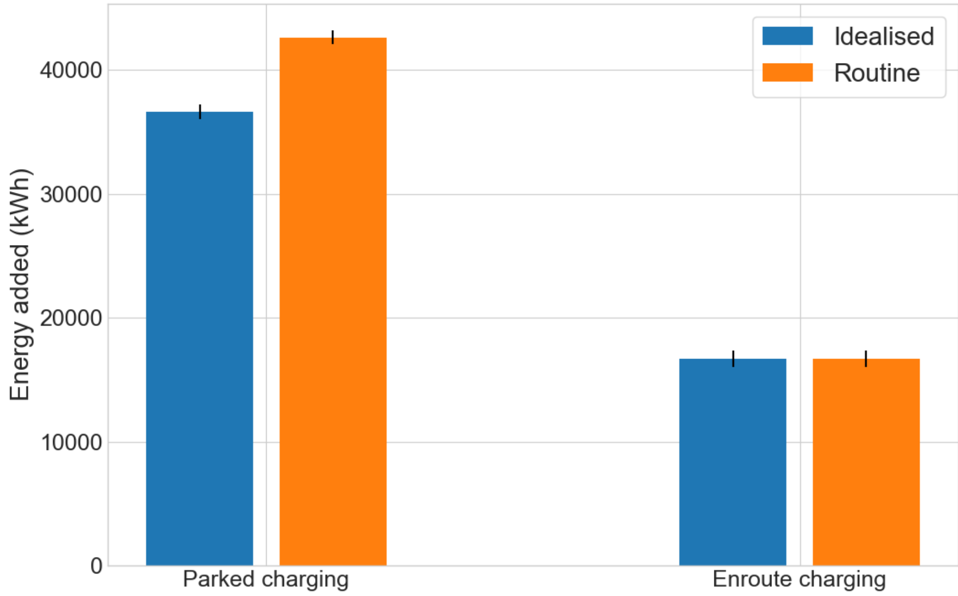

Figure 4.38: Total energy added to vehicles in Pollokshields network by different methods used to derive charging schedules for 100% penetration of EVs, 'base case' (all EVs 24 kWh batteries, low power charging scenario and H¬W¬P charging access)

Under the idealised schedule, EVs will take the least energy from parked charging events – i.e. at home, work and public destinations. Predictably, routine charging results in the greatest amount of energy taken from parked charging events. As they are both formed around the heuristic presented in Chapter 2, the energy taken from en route charging is the same for both.

Discussion

The idealised method might be prone to overestimating individuals' ability to effectively plan their charging activity, assuming that the week-long travel diary of a vehicle is known in advance. While this may not represent the actual charging habits of individuals, it is suggested as it was in Chapter 2 that individuals will exploit opportunities to charge when the vehicle would be parked anyway and their desire to minimise dependency on en route charging are likely to give comparable results in respect of inconvenience. Within the heuristic used to derive the charging schedules, the battery capacity and charger power will influence how drivers will plan their charging activities. This is shown to be an important factor of charging modelling: in the *Electric Nation* EV trial, it was concluded that EVs with larger batteries tend to charge less often (once per week as opposed to 3-4 times per week for smaller EVs) [186].

The routine method negates much of the effect of battery capacity on charging demand, as the EV will seek to replenish as much energy as it can regardless of the SoC remaining when it returns home from a trip. The routine method is a valuable quantification of the demand from EV charging if individuals were to plug their vehicles in every time they had a chance to. This approach to EV charging is often likened to the charging of a smartphone: regardless of the SoC it has at the end of the day, it is charged overnight as the act of plugging it in is of sufficiently low inconvenience. This type of charging is likely to be seen if V2G technologies are commonplace, in which EV drivers are financially encouraged to have their vehicles plugged in such that they can be remunerated for the provision of grid services such as energy arbitrage or frequency response.

Note that while the difference in results between the idealised and routine charging methods has been shown to be fairly slight for the base case, in which EVs' batteries are comparatively small, the difference becomes greater when these parameters change. This is evident from analysis presented presented in Section 4.7.

4.7 Effect of Population Socioeconomics on EV Charging Demand

In this section, the methodology presented in Section 4.3 is applied to both the Pollokshields and Gorbals study networks to examine the likely differences in resulting domestic and EV charging demand when distribution networks serve different areas.

4.7.1 Assignment of EV Parameters

In investigating the effect of the socioeconomic makeup of the area served by a distribution network on the resulting EV charging demand, assumptions were made as to the assignment of the EV parameters (battery capacity, charger power and level of access to charging at different locations) as explained below. The effect of these parameters on the resulting EV charging demand is explored in Section 4.8.

Although it is acknowledged that the socioeconomic makeup of an area may affect the parameters of the EVs in the area (e.g. wealthier areas may have a higher concentration of more expensive EVs, which may have higher battery capacities/charger power ratings), analysis of these differences is outwith the scope of this study and the assumptions regarding these parameters are the same for both study networks.

Battery Capacity

As was discussed in Section 2.4, 40-60 kWh is becoming a 'standard' battery capacity amongst newly-released EVs, though some early models and future budget models could have smaller capacities and luxury models are likely to have higher capacities. In this work, it is assumed that these 'standard' battery capacities will establish themselves as the most popular options, with some models of capacities either side of the mean (Figure 4.39). The effect of changing battery capacity on EV charging demand is examined in Section 4.8.

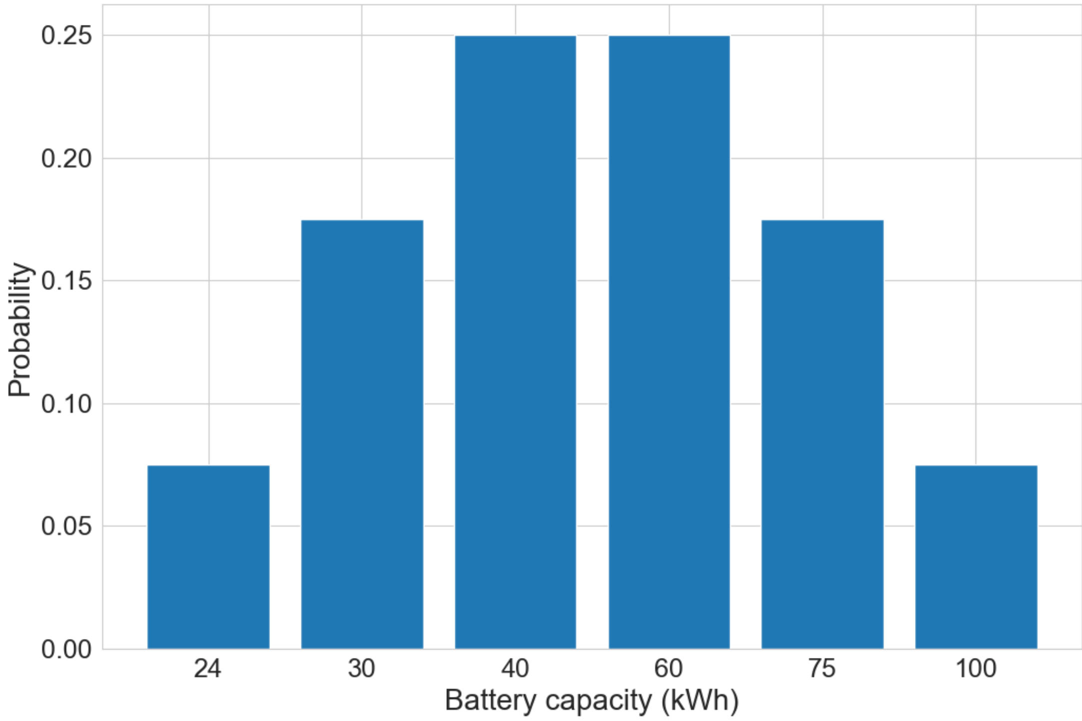

Figure 4.39: Probability distribution of assigned battery capacities (kWh) for study of EV charging demand impact on Pollokshields and Gorbals networks

Charger Power Rating

Charging power scenarios ('low' and 'high', as in Section 2.2) were used in this analysis. All EVs were assumed to have 7.4 kW charging capability, to reflect the trend towards higher power home chargers[8]. The effect of charger power on resulting network demand is explored in Section 4.8.

Access to Charging at Different Locations

As discussed in Section 4.3, these study networks were selected as they both have some form of dedicated resident parking at which charging infrastructure could be installed. Therefore, all vehicles instantiated in the network are assumed to have access to charging at home.

[8]in the UK, there is generally no difference in price between 'slow' and 'fast' home chargers – e.g. the WallPod EV charger retails at £320 in the UK for either 3.7 or 7.4 kW configuration [187] – thus it is likely that 7.4 kW chargers will soon become the norm.

Workplace charging is granted on a probabilistic basis, according to data from the individual dataset in the NTS (Figure 4.40). If a vehicle is returned as having a lead driver who is employed and drives their car to work, then there is a 75.9% chance that the vehicle has access to workplace charging under the assumption that all those who park their vehicles at work will be able to access charging. For all other combinations of economic activity and means of travel to work, it is assumed that vehicles do not have access to charging at work.

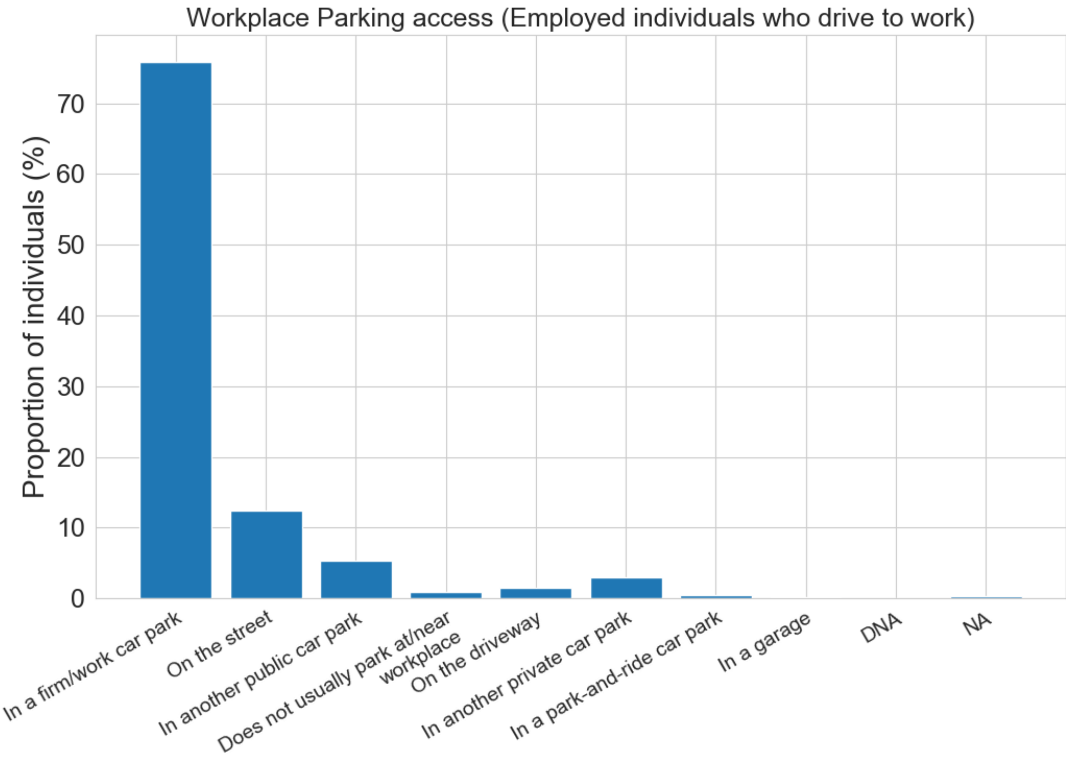

Figure 4.40: Proportion of employed/car – driver individuals (%) by parking at work – UK National Travel Survey (2002-16) respondents

In the absence of any data that could be used to suggest otherwise, it is assumed in this study that 50% of vehicles have access to charging at public locations (Table 2.3).

4.7.2 Analysis of Key Socioeconomic Indicators between Pollokshields and Gorbals Study Networks

Factors Influencing Domestic Demand

As inputs to the domestic demand model used (Section 4.4), variations in key socioeconomic indicators between the two study networks are shown in Figure 4.41. As demonstrated, there are distinct differences in the socioeconomic factors which are to affect the domestic demand of the consumers served by the study networks. The Pollokshields network is characterised by larger houses with the vast majority being owned. On the other hand, households in the Gorbals network are more likely to be smaller flats and while owned is still the most likely tenure, the proportion of private renters is more than double, and the proportion of social tenants is more than ten times higher than that of Pollokshields. Heating is much more likely to be non-electric than electric in both areas (typical of the UK as a whole), though the proportion of households with electric heating in Gorbals is around twice that of Pollokshields. The composition of households in the Pollokshields network is more likely to be larger than that of the Gorbals network: whereas the latter is characterised by a majority of single working-age adults and working-age couples, the former's most likely composition is a 3+ adults share with or without children. Larger families (2 or 3 children) are also more likely in Pollokshields than Gorbals. The SIMD deciles in Pollokshields range from 6 to 9, putting all households in the area in the 'least deprived' classification of the SIMD. The Gorbals network is split between SIMD deciles of 4 and 1, the latter being the lowest score attainable and therefore representing one of the most deprived communities in Scotland.

All of the comparisons, apart from the higher chance of electric heating in the Gorbals network, would suggest that the peak domestic demand per household in Pollokshields should be greater than in Gorbals. Section 4.7.3 presents results on the expected domestic demand in the two areas.

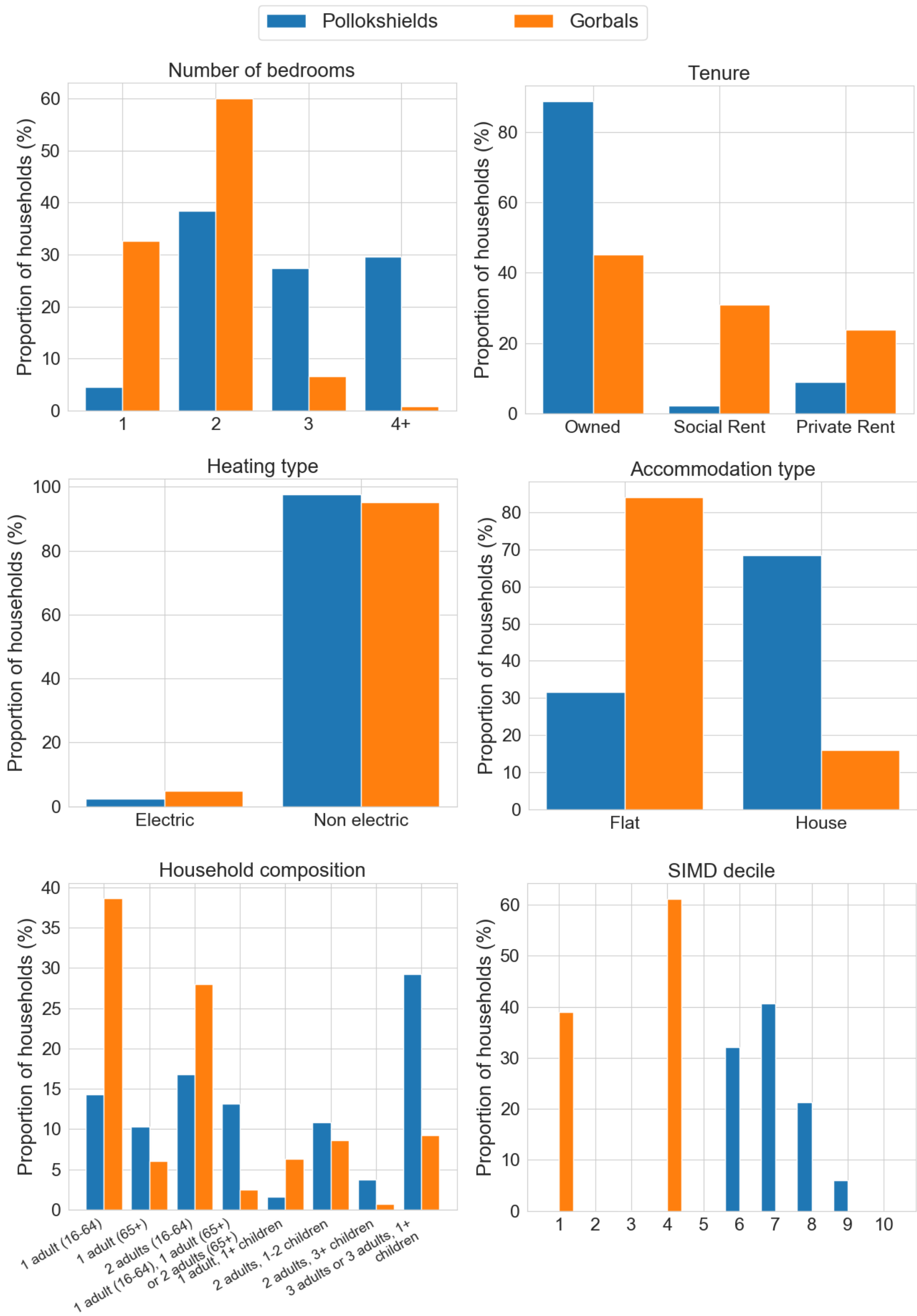

Figure 4.41: Factors influencing domestic demand in Pollokshields and Gorbals networks

Factors influencing EV Charging Demand

The inputs that affect how EV charging is simulated onto a distribution network are the number of vehicles (as one travel diary is assigned for every vehicle) and economic activity/means of travel to work informs which set of travel diaries is used (see Section 4.6.2 for analysis of the differences between these disaggregated subsets of NTS travel diaries).

Figures 4.42 and 4.43 show the variation in key socioeconomic factors that relate to EV charging demand.

Households in Pollokshields are more likely to have a greater number of vehicles than households in Gorbals; in Pollokshields, approximately 90% of households have at least 1 vehicle and nearly 50% have more than 1; in Gorbals, the most likely outcome is that there are no vehicles at the household and less than 10% of households have more than 1 vehicle. Employment is higher in Gorbals than Pollokshields, as is unemployment; in Pollokshields, a significant number of household lead members are reportedly self-employed or economically inactive, which can mean retired.

As previously discussed, whereas the Census economic activity question has four options, the NTS 'employment' question only has three: therefore, economically inactive individuals are assumed to have the same travel habits as unemployed individuals, following the assumption that the lack of a consistent employment shift pattern will be key in characterising their travel habits.

Whereas in the Pollokshields network the majority of employed individuals drive to work, there is a fairly even split between driving to work and walking to work for the employed individuals within the Gorbals network. It is most likely that self-employed individuals will drive to work in both areas, though a significant proportion will work from home. Though unemployed/economically inactive individuals in the Census data did answer with a means of travel to work, there are no corresponding travel diaries within these categories in the NTS, where any unemployed individual answered DNA to the means of travel question.

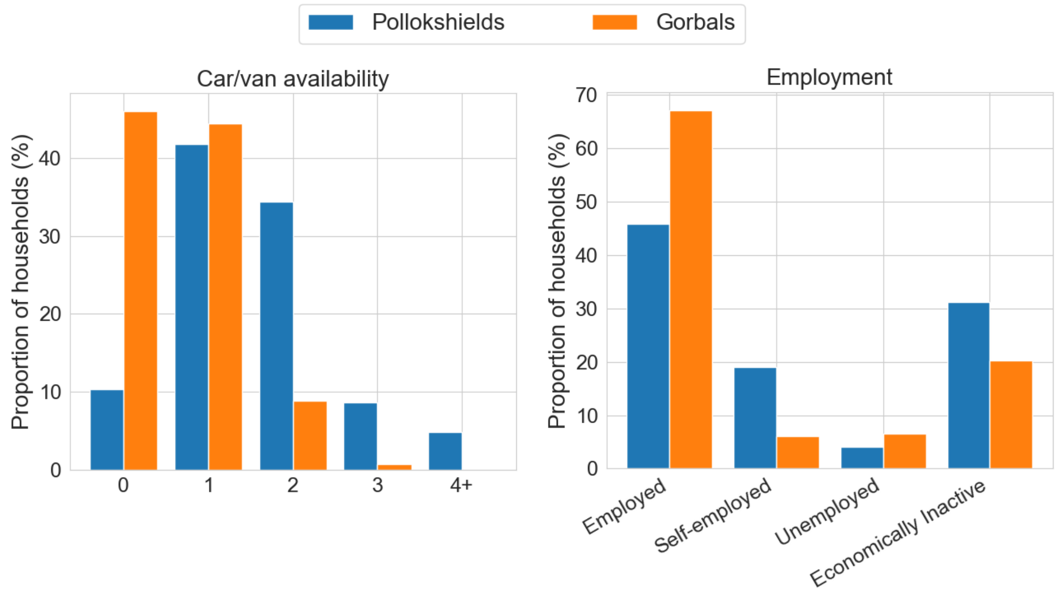

Figure 4.42: Factors influencing EV charging demand in Pollokshields and Gorbals networks

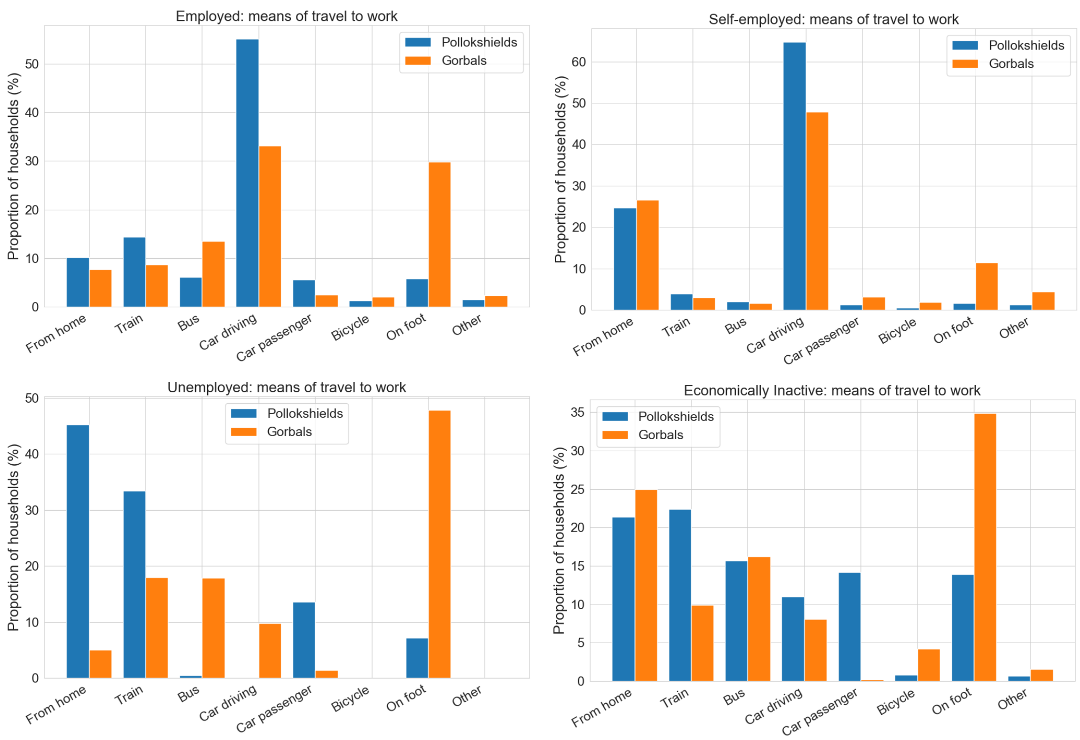

Figure 4.43: Means of travel to work by economic activity in Pollokshields and Gorbals networks

4.7.3 Expected Variation in the Impact from EVs between Pollokshields and Gorbals Study Networks

Number of Households and Number of Vehicles

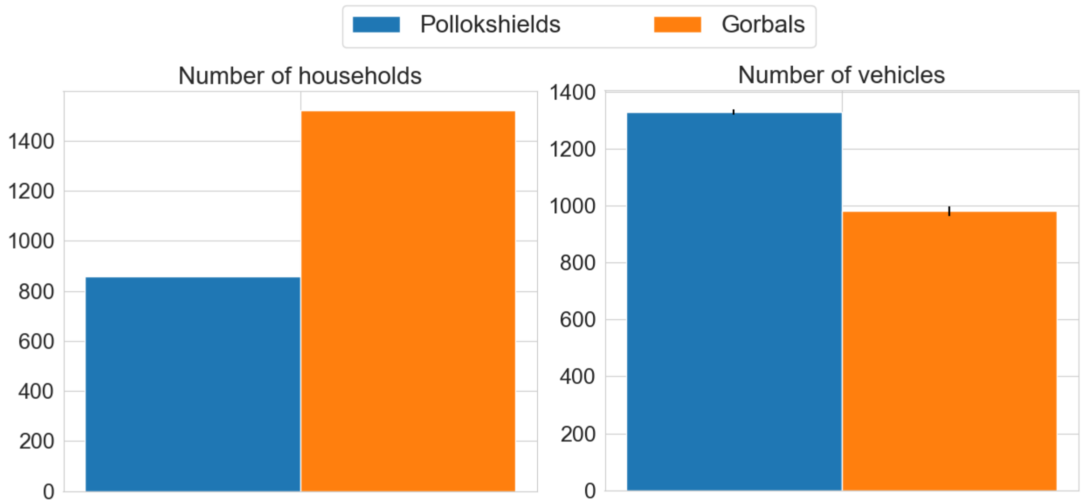

Figure 4.44: Number of households (left) and vehicles (right) in Pollokshields and Gorbals networks

Domestic Demand

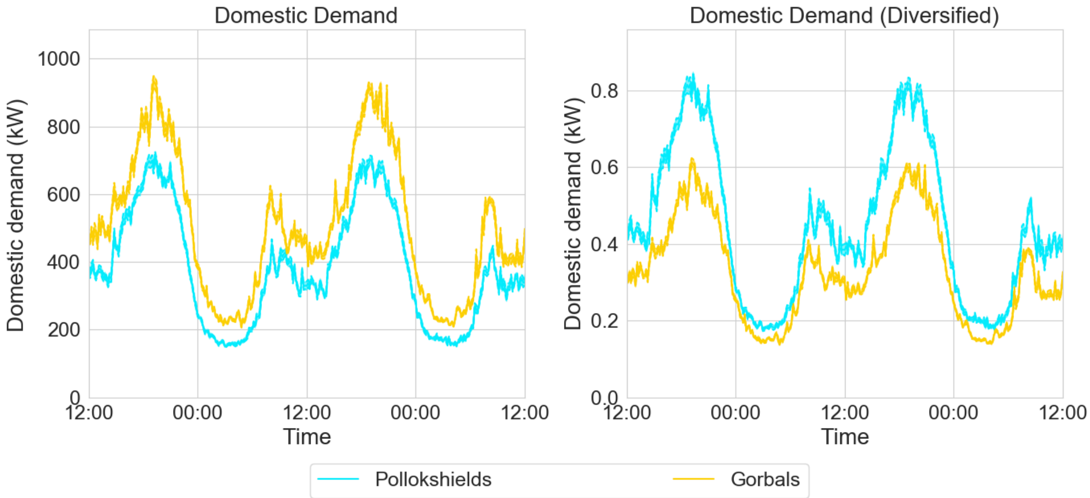

Figure 4.45: Total (left) and diversified (right) domestic demand in Pollokshields and Gorbals study networks from results of domestic demand model

Figure 4.45 shows that although the total peak network demand is expected to be greater for the Gorbals network due to there being nearly twice as many households (Figure 4.44), the domestic demand when diversified amongst the households in the network is expected to be higher in the Pollokshields network. This is in line with the presented results from the domestic demand tool used (Figure 4.5) and reflects the differences in socioeconomic indicators between the two networks (Figure 4.41).

EV Charging Demand

Figure 4.46 shows the charging demand for all three methods of deriving charging schedules from travel data for the Pollokshields and Gorbals networks. This charging demand is added to the domestic demand in Figure 4.45 to produce Figure 4.47, which shows the total network loading before and after 100% penetration of EVs. In accordance with results presented in Section 4.6.4, 10 trials were conducted for each method of deriving charging schedules from travel data for each network.

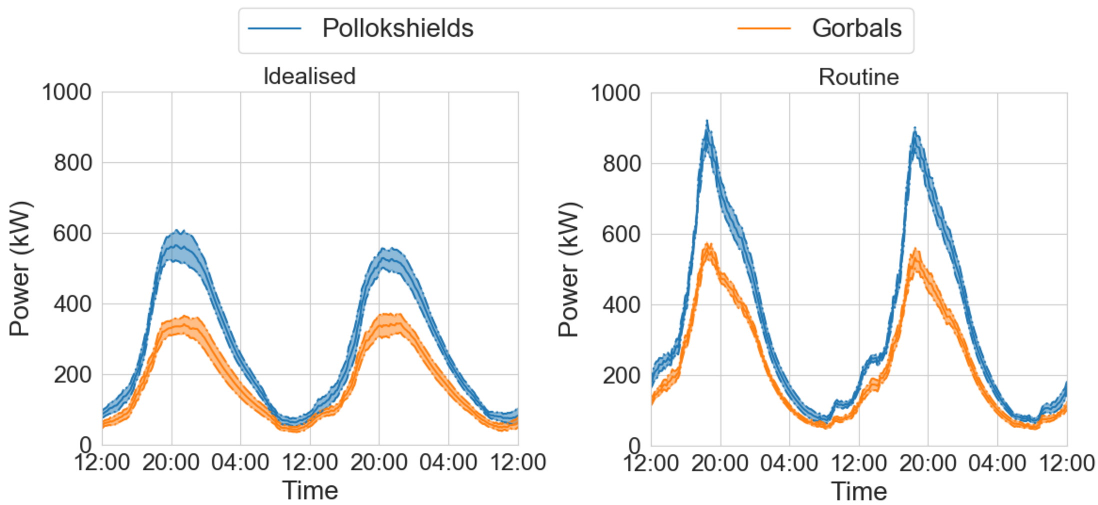

Figure 4.46: EV charging demand for 100% penetration of EVs by different method to derive charging schedules, Pollokshields and Gorbals networks

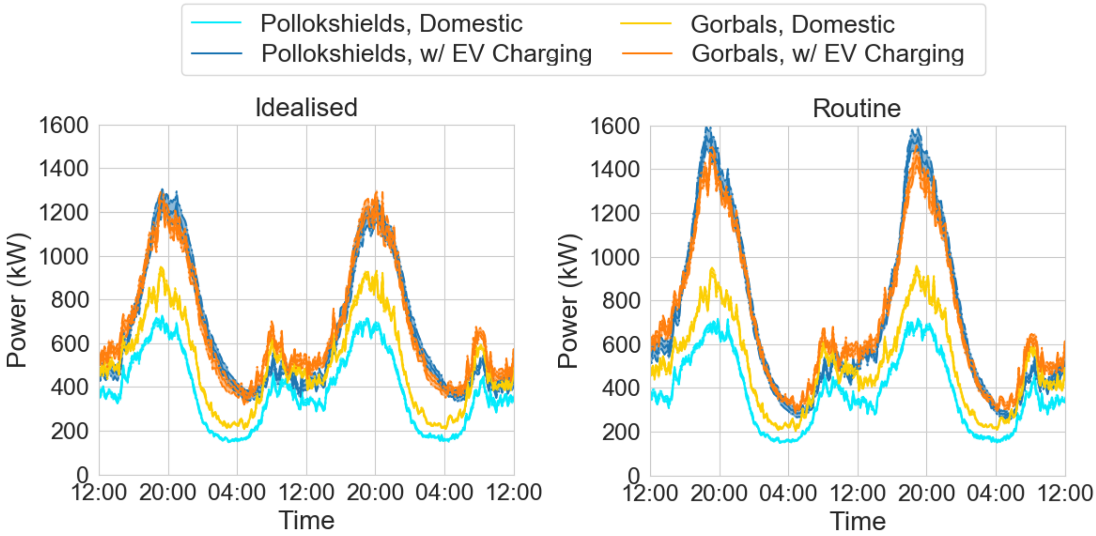

Figure 4.47: Domestic demand and domestic demand plus EV charging for 100% penetration of EVs by different method to derive charging schedules, Pollokshields and Gorbals networks

4.7.4 Discussion

Figure 4.46 shows that the charging demand peak is expected to be significantly greater in the Pollokshields network than the Gorbals network, ranging from a 50% increase from approximately 300 kW to approximately 450 kW in the idealised case to a 65% increase from approximately 550 kW to approximately 900 kW in the routine case. An increase in peak demand could be expected purely due to the significantly greater number of vehicles present in the Pollokshields network (Figure 4.44). However, the number of vehicles in the Pollokshields network is only approximately 40% greater than the number of vehicles in the Gorbals network, suggesting that is is more than just the number of vehicles that influences their total charging demand. The additional difference in charging demand is suggested to be as a result of the differences in how these vehicles move around.

Figure 4.48 shows histograms of the total travel diary distances of EVs in both networks for all 10 trials carried out. Figure 4.49 shows the energy added per vehicle in parked and en route charging events, and the 'spent energy' (i.e. the energy required by the vehicle to complete its weeklong travel diary) for all three methods of deriving charging schedules from travel data, for both study networks. Figure 4.50 shows the frequency of charge events by charge start time in 30 minute intervals for all three methods of deriving charging schedules from travel data, for both study networks.

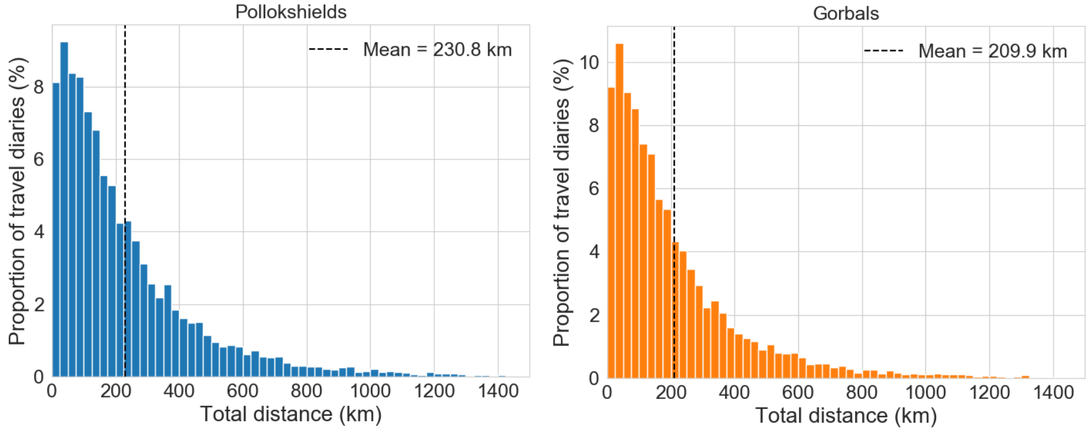

Figure 4.48: Total distances in UK National Travel Survey (2002-16) travel diaries, Pollokshields and Gorbals networks

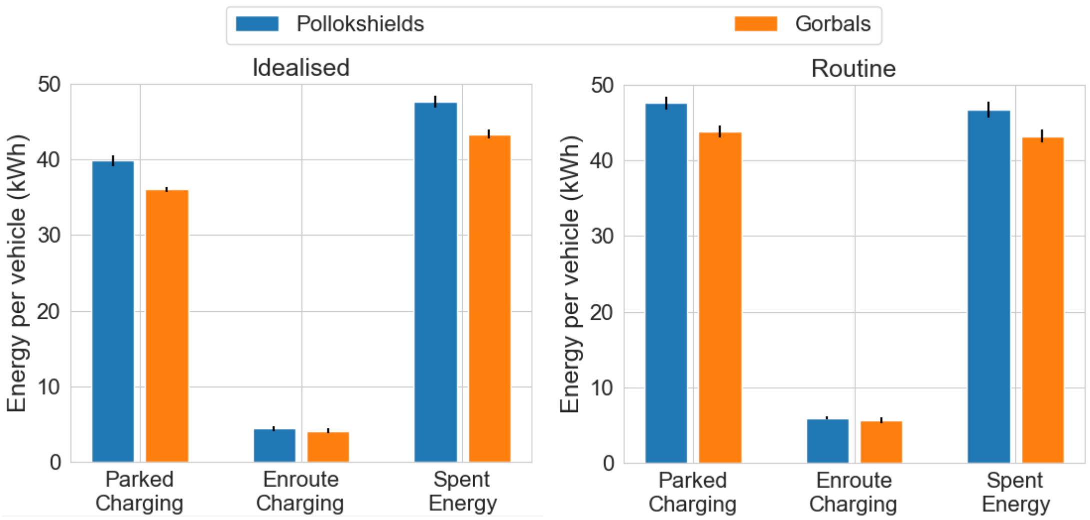

Figure 4.49: Energy added per vehicle for parked and en route charging events by different methods to derive charging schedules for 100% EV penetration, Pollokshields and Gorbals networks

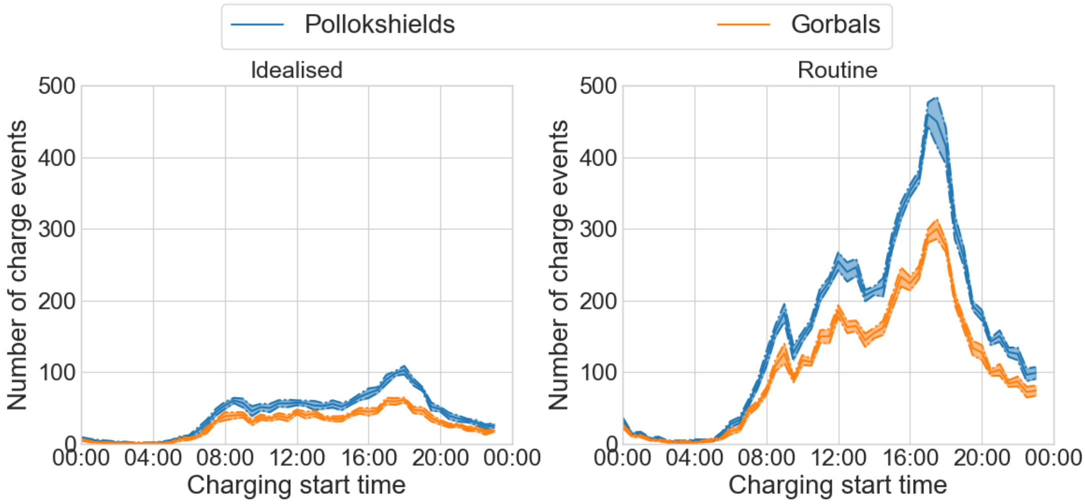

Figure 4.50: Number of charge events by charge event start time for different methods to derive charging schedules for 100% EV penetration, Pollokshields and Gorbals networks

It is apparent from Figures 4.48-4.50 that EVs in the Pollokshields network are not only expected to be driven further and therefore require more energy, but are also expected to be disproportionately more likely to start charging in the evening around 17:00-19:00, where the network is already at its most highly loaded. It is suggested that both of these differences are likely due to the greater proportion of individuals who drive to work in the Pollokshields network compared to the Gorbals network (Figure 4.43) which, as previously shown in Figure 4.26, would be expected to lead to a greater number of drivers arriving at home in the evening.

One drawback of the approach used in this section is that detailed geographical information is not available in the NTS. It could be expected that individuals who live closer to places of employment or local amenities (for example, those who reside in inner city areas such as the Gorbals network) would travel lesser distances than those who live further away (for example, those who reside in suburban areas such as the Pollokshields network, or rural dwellers). It is suggested for future work that analysis be carried out to further disaggregate charging habits on the basis of geographical location and demographics. This is further discussed in Section 6.2.

One particularly noteworthy result, by comparing Figure 4.47 with Figure 4.32, is that for the idealised charging schedule, the total EV charging demand has decreased as a result of a wider spread in parameters, versus every vehicle having a 24 kWh battery and access to home charging only at 3.7 kW. However, for the routine charging method, it has stayed much the same. Of course, for the routine charging method, the charging schedules are less dependent on EV parameters such as battery size and charger power as the vehicle will plug in regardless of its SoC and the energy demand is dictated only by the travel diary. The effect on changing EV parameters is explored in the next section.

4.8 Effect of Technical Parameters on Electric Vehicle Charging Demand

In this section, the influence of changing the three EV parameters formerly analysed in Chapter 2 and earlier in this chapter (battery capacity, charger power and level of access to charging) on the resulting charging demand is investigated.

The analysis presented in this section is for 10 trials of the Pollokshields network for 100% EV penetration. The idealised charging method is used in this section as the resulting charging diaries differ significantly when the parameters are changed. As already mentioned, this is in line with EV trial results; preliminary results from the *Electric Nation* trial [186] having found that EVs with larger batteries are significantly less likely to be plugged in 'routinely' (every time the vehicle arrives home) than those with smaller batteries.

4.8.1 Electric Vehicle Charging Parameters

Battery capacities found on variants of three EVs spanning typical battery sizes and levels of energy consumption on the global market are used for reference: the lower-range first generation Nissan Leaf (24 kWh), the 64 kWh version of the mid-sized Hyundai Kona Electric and the longer-range 100 kWh version of the Tesla Model S. The energy consumption values used are taken from the US EPA's fuel economy test data as in Figure 2.3. Values used for this study are shown in Figure 4.51 along with battery capacity for the vehicle models discussed.

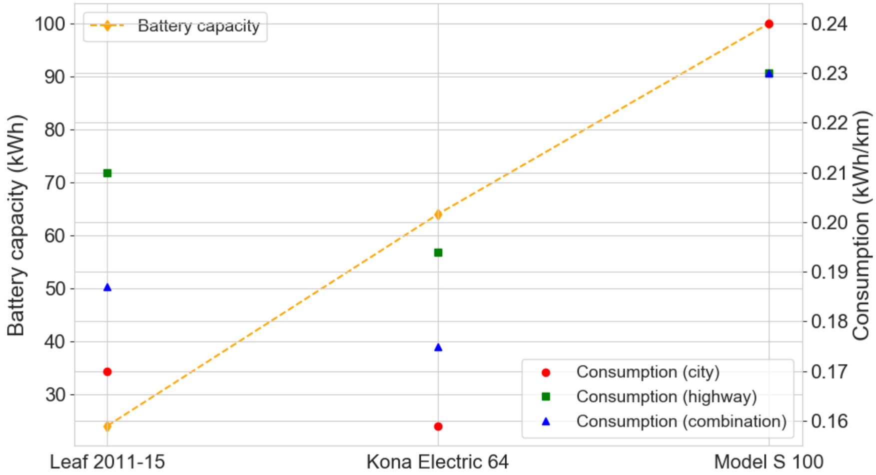

Figure 4.51: Energy consumption values (city, highway and combined) for vehicles considered in study, source: US Environmental Protection Agency

Charger power and level of access to charging are investigated as per the same levels as they were in Chapter 2 (see Tables 2.2 and 2.3 respectively).

4.8.2 Results

Figure 4.52 shows the time series of charging demand from each mode of charging, Figure 4.53 shows the time series of domestic demand (generated using the same method as presented in Section 4.4) and domestic demand plus home charging, Figure 4.54 shows the time series of the proportion of EVs in the network i) charging and ii) charging in the CC mode of the battery charging profile (Figure 2.6) and Figure 4.55 show the total energy extracted from each charging type over the seven day period – for all combinations of EV parameters trialled. The titles of each plot refer to the battery capacity (kWh), the charging power scenario (low/high) and level of access to charging at different locations: H, W and P refer to access to charging at home, work and public destinations respectively and a ¬ symbol preceding any of those letters implies a lack of access to charging at that location. Charts in all figures show the spread of the results across the 10 trials carried out: in Figures 4.52-4.54, the shaded regions show the 95% confidence intervals of the loading or charging coincidence at 10 minute intervals and the solid lines show the mean values. In Figure 4.55, the mean values are shown by the height of the bars; 95% confidence intervals are shown by error bars.

All results presented in this section are shown for an EV penetration of 100%.

Network Loading Time Series

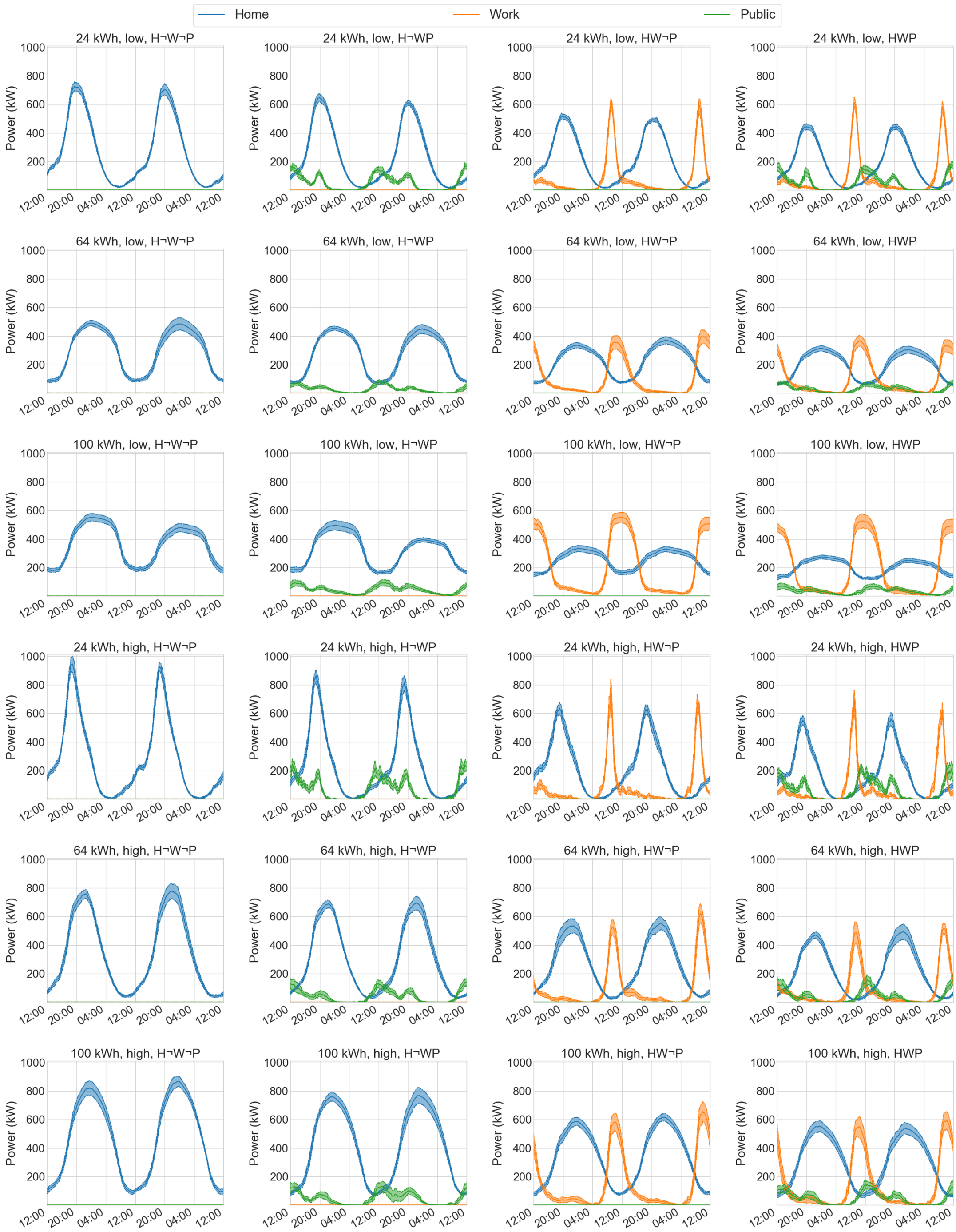

Figure 4.52: Time series of home, work and public charging demand for varying combinations of battery capacity, charger power and levels of access to charging at different locations

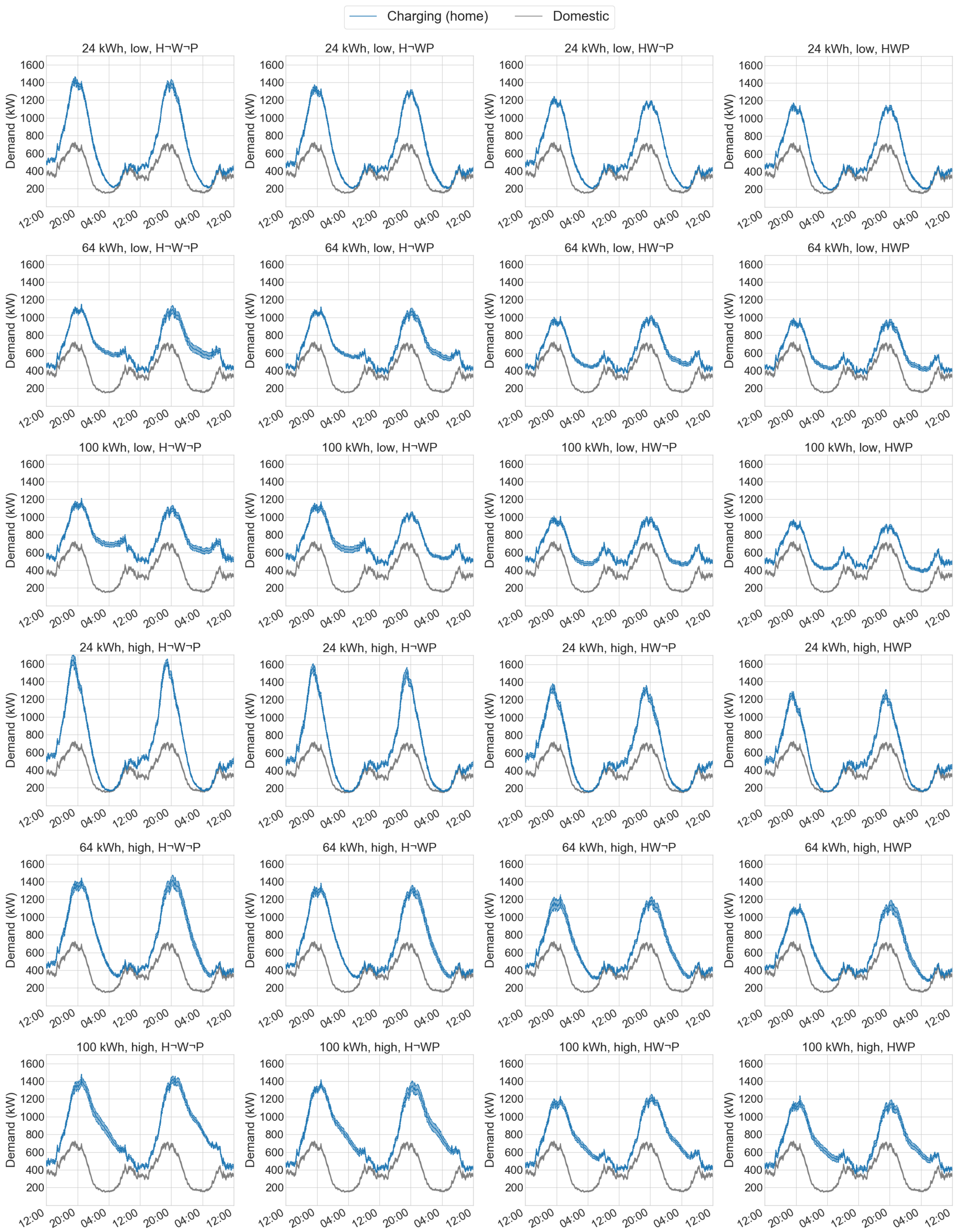

Figure 4.53: Time series of domestic demand and domestic plus home charging demand for varying combinations of battery capacity, charger power and levels of access to charging at different locations

Coincidence of Charging

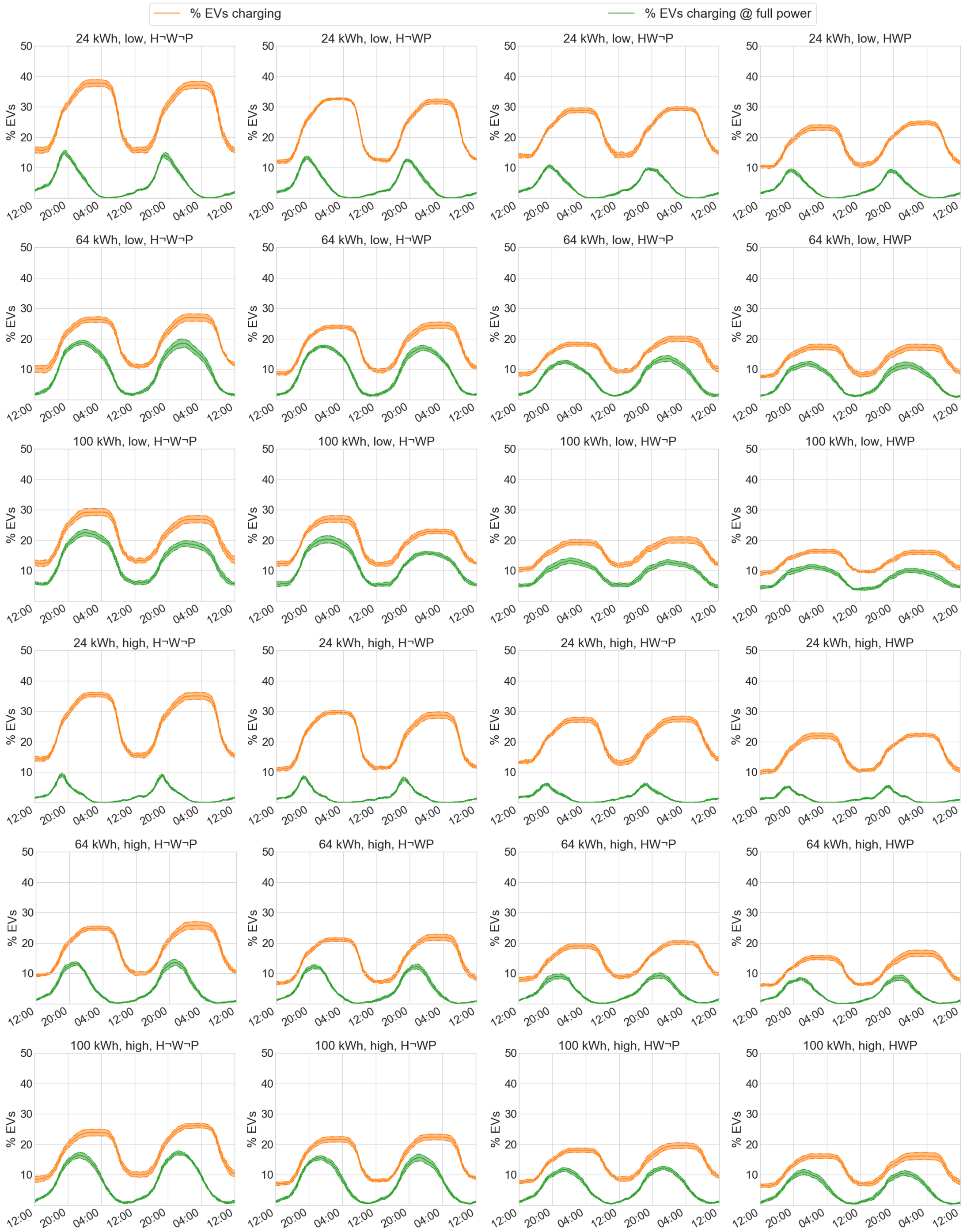

Figure 4.54: Coincidence of EVs charging and coincidence of EVs charging at full power for varying combinations of battery capacity, charger power and levels of access to charging at different locations

Energy Added

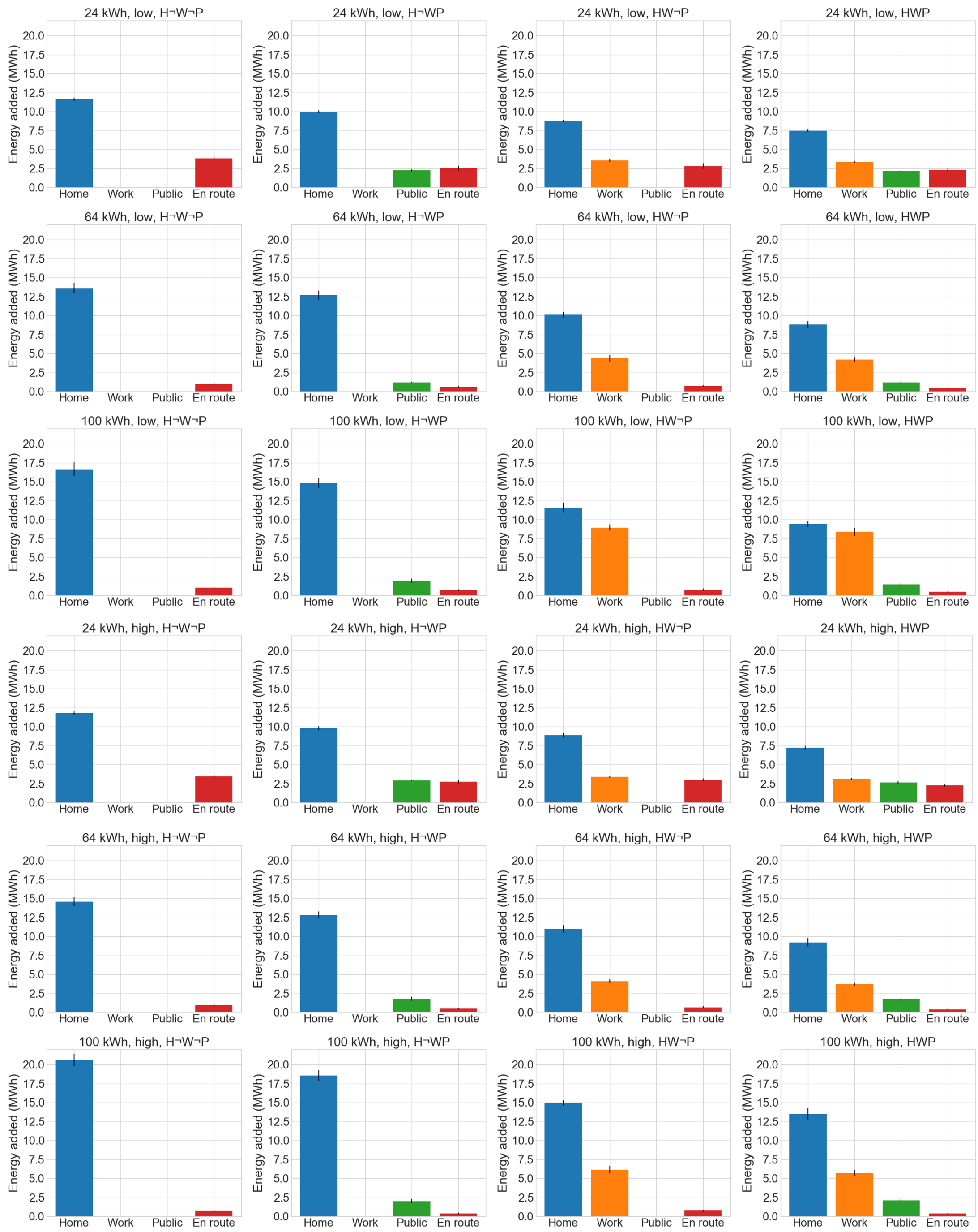

Figure 4.55: Total energy added to vehicles by charging at home, work, public and en route for varying combinations of battery capacity, charger power and levels of access to charging at different locations

4.8.3 Discussion

Effect of Battery Capacity

Figure 4.52 shows that increasing the battery capacity for a given charger power and level of access to charging reduces the prominence and magnitude of the peak, with a 30% reduction in peak charging demand from having a fleet of 24 kWh EVs to having a fleet of 64 kWh EVs. Notably, the peak demand also occurs later when battery capacities are larger: using the low power, H¬W¬P scenario as an example, the peak demand recedes from around 8 pm if all vehicles had 24 kWh batteries to around midnight for both 64 kWh and 100 kWh cases. Figure 4.53 shows that increasing the battery capacity for a given charger power and level of access to charging leads to the shifting of charging demand late into the night, resulting in a higher load on the network at off-peak times.

These patterns are explained by the patterns of EVs plugging in, as shown in Figure 4.54. As previously discussed, EVs with larger battery sizes are expected to charge less often – but when they do charge, their energy requirement per charge event is expected to be greater. This means that the proportion of these vehicles that are charging at full power (in the CC region of the charging curve) is higher as these vehicles take longer to fill up their batteries. The result is a later peak and a smaller difference between peak and trough.

Figure 4.55 shows that in terms of the total energy added to the vehicles, an increasing battery capacity causes a reduction in the energy added from en route charging, as the increased driving range of the vehicles means that they are less likely to be forced to charge en route. The total amount of energy varies according to the level of energy consumption applied to each battery size.

The effect of battery size on EVs' charging demand is shown to have a saturating effect; while there is a significant difference between 24 kWh and 64 kWh, there is no discernible difference in the magnitudes of the peaks between 64 kWh and 100 kWh. This is likely due to the relationship of the driving range of the vehicles with the distance of the trips that the vehicles actually complete. As shown in Figure 4.24, approximately 50-80% (depending on economic activity and means of travel to work) of travel diaries recording less than 200 km of driving distance. The relative EPA real-world ranges of the three representative vehicles used for this study are 121 km for the 24 kWh Nissan Leaf, 415 km for the 64 kWh Hyundai Kona and 507 km for the 100 kWh Tesla Model S [38]. It is suggested that the relative frequency of parked charging opportunities with that of journeys undertaken seems to produce this saturating effect.

Effect of Charger Power

Figure 4.52 shows that increasing the charging power increases the prominence, magnitude and ramp of the peak demand for a given battery size and level of access to charging. On the other hand, the minimum charging demand is reduced: in most cases, to near-zero in the middle of the day. The timing of the peak is brought forward: using the H¬W¬P scenario as an example, the peak for the 24 kWh case is brought from 8 pm to 7 pm and the peak for the 64 kWh and 100 kWh cases are brought from midnight to around 10 pm. Similar patterns are observable from Figure 4.53: an increase in charging power brings charging demand forward to be coincident with the existing domestic demand peak, resulting in the highest overall demand to the network coming from a fleet of EVs with 24 kWh batteries, high charging power and access to charging at home only.

Figure 4.54 shows that the proportion of EVs charging through the night is expected to reduce slightly if charging power is increased, and the proportion of EVs charging at full power is expected to reduce significantly. This is because vehicles will fully charge their batteries in a shorter time if they have access to a higher charger power.

Figure 4.55 shows that there is no significant change in the energy added to vehicles when changing the charging power. This suggests that the majority of parked charging events are long enough to fill the vehicles' batteries even with the low power charging scenario.

Effect of Charging Access

It is shown in Figure 4.52 that increasing the level of access of charging at different locations can significantly reduce the home charging peak, and thus the peak that the study network concerned would experience, as shown in Figure 4.53. This is done at the expense of an increase in demand in work and public location charging. Of particular interest is workplace charging, which in most scenarios is seen to be the new peak demand of all charging modes. This is due to the generally smaller variance in the time of arrival at work compared to the time of arrival at public places.

Figure 4.54 shows that being able to charge at other locations significantly reduces the proportion of EVs charging at home overnight; a similar effect is observable on those charging at full power.

Figure 4.55 shows that increasing the number of locations that individuals can charge at spreads the energy added across different charging types. A reduction in en route charging is seen, due to individuals being less likely to have long stretches without parked charging opportunities. It is shown that as when the en route charging energy reaches a certain level, it does not get any smaller. It is suggested that this is due to the presence of long journeys, which outstrip the range of vehicles and force them to stop and charge. Home charging remains the majority of charging for all cases, which is in line with predictions made in [135].

Discussion of Results in Context of EV Markets and Electricity Networks

As the EV market continues to evolve, it is proposed that the resulting impact to the electricity system – as characterised by Figures 4.52-4.55 – will move towards increasing battery capacity, increasing charging power and access to charging at more locations as discussed in Section 2.4.

GB peak domestic electricity demand generally occurs between 6-7 pm when cooking, lighting and audiovisual demands are increased generally when people get home from work [188–190]. Therefore, EV charging will have the greatest network impact when the peak demand from charging coincides with the peak domestic demand. Figure 4.52 shows that an increase in battery capacity could make it easier for distribution networks to provide peak EV charging demand, given that it is more likely to occur later on when domestic demand is lower. Increasing charger power, however, could bring greater challenges to the distribution system as the peak from EV charging is seen to increase significantly and be brought towards the existing network peak. Aside from providing a means of charging for those who lack access to charging at home, the results presented should provide a mandate for increasing the penetration of workplace and public destination charging as a method of reducing the latent peak demand on residentially-dominated distribution networks.

4.9 Chapter 4 Conclusions and Further Work

This chapter has presented an investigation of the impact of residential EV charging on distribution networks. From reviewing the literature in Section 4.2, it was established that in simulating the impact of EV charging on networks, the most advanced methods used either results from EV trial data or raw travel data from which to generate sets of charge events. It was established that the author found no works that modelled EV charging behaviour in a way that allows drivers to take the option to not charge, given an opportunity to do so. It was also established that while there are several works in the literature that are focused on simulating EV charging on real distribution networks, there are none that the author has found that use local socioeconomic datasets to inform the likely travel habits of the individuals who charge their vehicles within these networks.

In Section 4.3, a sociotechnical model was presented which combines real network data from the relevant network operator with Census and SIMD data relating to the households served by the network. An established domestic demand model as presented in [173, 174, 180] was adapted for use in this study to provide domestic load profiles for the households in the network area, based on the building type data, SIMD decile and distributions of Census data of the output area in which the household is situated.

The impact of EV charging was simulated using both EV trial data (from the MEA EV trial) and travel data (from the NTS 2002-16), demonstrated in Sections 4.5 and 4.6 respectively.

Using the EV trial data enabled a case study of the network if all vehicles within the network were of battery capacity 24 kWh, had access to 3.7 kW home charging and their charging behaviour was assumed to resemble that of the 215 participants in this particular trial, given that an unknown proportion of their charging was curtailed by the 'Esprit' technology (Figure 4.6). Following this case study, the Pollokshields study network would be expected to see up to a 65% increase in its evening peak loading if every vehicle in the network was swapped for an EV. It was found that the impact on network assets would begin to be unacceptable when EV penetration reaches 40-70%, in that a subset of transformers and lines in the network would exceed 50% loading and the voltage at customer endpoints would dip below 0.94 pu, outwith GB statutory voltage limits.

The main advantage to using EV trial data is that it negates the need for complex modelling of human behaviour and how likely people are to charge their vehicles given a set of circumstances. However, the quantity of EV trial data published at the time of writing is not sufficient to conduct meaningful analysis that appreciates the significant effects of the changing technology in the EV sector (namely battery capacity, charger power and access to charging) or the travel habits of the individuals behind the wheel. As a result, any analysis using EV trial data would tend towards that presented in Section 4.5: a case study based on a narrow subset of individuals using a narrow subset of vehicles.

To enable the investigation of the effects of varying socioeconomic indicators and of varying EV parameters on the resulting impact on the network, Section 4.6 presented two methods on deriving charging schedules from week-long travel diaries available from 15 years of NTS data, with the intention of covering the probable spread in drivers' charging habits. The idealised method was based on the heuristic used to find the minimum number of possible charge events given a set of required trips as used in Chapter 2. The routine method was based on the idealised method, though individuals would now always plug in upon arriving home (if they had access to charging at home).

The idealised method might be prone to overestimating individuals' abilities in knowing their own travel habits a week in advance and selecting the charge events that would lead to them having to charge the least often – though, as previously discussed in Section 2.1.3, smartphone apps such as Zap-Map's journey planner have recently become established to assist drivers in becoming more efficient at planning charging schedules with minimum effort. The result is that it represents a scenario in which the driver takes the least possible amount of electrical energy from the network in order to satisfy their (known) travel needs (as clearly depicted in Figure 4.38). On the other hand, the routine method represents a scenario where the act of plugging in at home is considered to be of minimal inconvenience and it is done out of a routine habit. This could represent a scenario in which individuals are incentivised to plug their vehicles in, for example if they are to be used as a flexible resource for the benefit of the grid. Whereas EVs will plug in at home regardless of their SoC under the routine case, and therefore their behaviour is not very dependent on the technical parameters of the vehicle, these parameters have a significant bearing on the results of charging demand when drivers charge under the idealised model.

In Section 4.6.4, the results of the simulations using EV trial data are compared to simulations using NTS travel diaries with all three methods of modelling individuals' charging behaviour with the same set of parameters: all EVs with 24 kWh batteries and access to charging at home only at 3.7 kW. It was found that the total network loading from the simulation using NTS travel diaries was remarkably similar – in terms of the temporal variation of demand – to that from the simulation using MEA data, with the peak occurring within the window 18:00-20:00 for both. The loading was found to be around 15-25% higher when using the travel diaries; this is suggested to be attributable to the management of charging load by the 'Esprit' technology (Figure 4.6) and the unknown quantity of missing charge events in the dataset. When comparing the different methods of generating charging schedules from the travel data for this specific case study (i.e. 24 kWh batteries, charging at home only at 3.7 kW), the routine method resulted in the greatest peak as could be expected, though the margin was relatively slight for this specific case study.

Section 4.7 presents an investigation into the effect of population socioeconomics on the resulting EV charging demand by presenting two study networks, Pollokshields and Gorbals, with differing characteristics according to those used in this study (Section 4.3.4). It was found that whereas there are expected to be around 40% more vehicles in the Pollokshields network compared to the Gorbals, the increase in EV loading is expected to be 50-65% higher: therefore, it can be concluded that the impact of EV charging is due to more than just the number of vehicles present. It was shown that vehicles in the Pollokshields network would be more likely to travel further distances (and hence require more energy) and are disproportionately more likely to plug in during the evening when the network is at its most loaded. This is likely due to the higher rate of individuals who report using their car as a means of travel to work in the Pollokshields network compared to the Gorbals. Therefore, network planners should take into account the socioeconomic make-up of an area when planning for an increase in demand due to the uptake of EVs. Furthermore, the implications surrounding the cost of network upgrades and how they might be shared are important. This is further discussed in the Epilogue of this thesis.

Section 4.8 presents an investigation into the likely effect of changing EV parameters on the resulting charging demand if drivers plan their charging schedules according to the idealised method (as has been found in preliminary results of the *Electric Nation* EV trial [186], increasing battery size has been found to lead to a reduction in the frequency of charge events). It was found that out of the key emerging patterns identified in the evolving EV market, increasing battery capacities and the establishment of more widespread charging opportunities may reduce the peak demand from EV charging or shift it to a time less likely to coincide with peak domestic demand, hence making it easier for the network to cope with increasing penetrations of EVs. On the other hand, increasing charging power may increase the peak and bring it closer to a time where it is more likely to coincide with peak domestic demand, thus making it more difficult for the network to cope.

A common theme in this chapter is that a high penetration of EVs is likely to present problems to the distribution network and, although this is likely to vary based on socioeconomic characteristics of the network in question and certain changes in technologies relating to the sector, it is clear that there are sets of circumstances which would lead to severe consequences in terms of overloading and undervoltages, both of which could have disastrous consequences in terms of security of supply and, in the worst case, public safety. Therefore, it is necessary that residential EV charging be managed in a way that safeguards the operation of the network (or minimises the cost of any necessary upgrades), yet allows maximum utility from the network to the individuals that will use these vehicles to get around. This will be explored in Chapter 5.

Chapter 5

Opportunities for 'Smart' Charging

5.1 Introduction

5.1.1 Motivation

It was shown in Chapter 4 that, if their charging is uncontrolled, a high penetration of EVs is likely to present problems to the distribution network. The topic of controlled (a.k.a. 'smart') EV charging has long been talked about as a potential solution for the integration of EVs into the power system, owing to the flexible nature of their demand. As of July 2019, it is mandated that every installation of EV charging infrastructure eligible for government grants in GB should be 'smart', i.e. 'have the capability to receive, interpret and react to a signal' [191]. However, it is not yet clear how this will be done or upon what set of technologies it will be based. Therefore, there exists a substantial space for research into what the most effective method of controlling EV charging may be.

In addition to enabling charging within network limits, smart charging has the potential to allow EVs to interact positively with the power system, particularly by reducing the carbon emissions associated with their charging and absorbing excess RES generation (that would otherwise be wasted).

5.1.2 Contribution

This chapter seeks to evaluate the potential of various methods of controlled charging to manage the impact of EV charging on distribution networks. A method for the formal optimisation of EV charging is presented, using a time-coupled linearised approximation of the optimal power flow (OPF) problem, given sets of charge events derived from distribution network models as per analysis presented in Chapter 4.

Two use cases of this optimisation are presented:

1. An investigation of the potential of controlled EV charging to minimise the impact on the distribution system via a 'valley filling' technique to solve the over-loading issues found on the Pollokshields network as presented in Chapter 4. Given that such an optimisation is based on the agent doing the control of the charging (e.g. an aggregator) having a perfect foresight of future arrivals of EVs, their energy requirements and their departure times, its realisation in a real smart grid is unrealistic. To this end, this chapter presents a series of simpler, low-information heuristic methods for controlling charging based on a level of data that could be obtained from 'smart' (see definition above) EV chargers. A comparison is made between the outcome of using these heuristics and the 'best case' represented by the formal optimisation.

2. An investigation of the potential of controlled EV charging to enable further decarbonisation of the grid, via two case studies on different scales: i) an investigation of the potential of smart charging in reducing the CO_2 emissions associated with EV charging by selectively charging when grid carbon intensity (CO_2/kWh) is low, and ii) an investigation into the potential of large fleets of EVs to provide demand in times of excess wind generation, hence reducing the proportion of wind generation that is wasted.

5.2 Literature Review

The control of EV charging is a well-practised area, both in terms of the volume of academic literature published and the attention given to it as part of publicly-funded

EV trials.

The review of the works presented in this section is divided into three subsections. Section 5.2.1 presents a review of academic literature concerning the minimisation of system or consumer cost; Section 5.2.2 focuses on the academic literature concerning the integration of RES and EVs; Section 5.2.3 discusses examples of the control of EV charging as seen in UK-based EV trials.

5.2.1 Optimising Charging for the Minimisation of System and Consumer Cost

The majority of works in the academic literature focus on controlling the charging of EVs for the benefit of the network and its operation. In [192], the authors present a concept they call 'real time smart load management', in which the sum total of charging power at any moment is restricted to the rating of the secondary transformer. There are three groups of EVs, each assigned a priority of charging: those with the highest priority are the only EVs allowed to charge during peak time (taken as 18:00-22:00). The paper uses a mixed integer linear programming (MILP) optimisation method to minimise the total cost of generation and losses subject to the EVs' energy demand being met and, in doing so, ensures that the valleys of demand are filled. [193] presents an MILP approach to scheduling energy to and from a fleet of EVs, with associated charging and discharging costs: the result being the minimum cost of network operation from the combined perspectives of a system operator and an aggregator. [194] presents a heuristic algorithm that seeks to use EV charging to flatten the demand profile of the local grid transformer, given assumptions about when vehicles in a fleet of EVs are likely to arrive and leave. [195] presents the minimisation of charging cost amongst a fleet of EVs via a greedy algorithm: a changing spot price of electricity is used such that each EV will choose the lowest price regions in which to charge a pre-defined amount of energy, which is derived from statistical analysis of an Australian travel survey. [196] presents a decentralised approach to charging optimisation, in which a utility sends a control signal to each vehicle in turn in a fleet of EVs, which establish a charging profile that delivers the required amount of energy in the charging window representing their length of stay; the control signals sent to each EV are based on what would be required to flatten the total demand profile (domestic demand plus EV charging demand).

There are works in the literature that are based on controlling EV charging for the benefit of the consumer, or an aggregator which nominally represents the consumers' interests. [197] presents a minimisation of a convex objective function which represents the total cost to individual EV owners of charging and discharging their vehicles, subject to a changing electricity price (which is not affected by an increase in EV charging demand). This price can go negative, which is the only circumstance under which the EVs would discharge. As recognised by the authors, this relies on knowledge of EVs' duration of stay and required energy. Furthermore, if a low spot price triggers all connected EVs to suddenly start charging, this would give a spike in demand which would, if large enough, lead to a perturbation in system frequency. [198] proposes a method to optimise the scheduling of EV charging in order to minimise the cost of charging to the those EVs. While this work presents a dynamic approach in which the fleet of EVs is adjusted in real time each time an EV starts or finishes charging, the model requires knowledge of the charging window of each EV in the fleet. [199] presents a heuristic approach to the optimisation of EV charging scheduling such that the EV drivers maximise their revenue from the provision of ancillary services, including a cost associated with use of the battery to model its degradation.

5.2.2 Optimising Charging for the Integration of Renewable Generation

The integration of REs and EV charging via mathematical optimisation has also received considerable attention. Amongst the works reviewed in this section, optimisation techniques range from convex programming (CP) [200] to linear programming (LP) [201] and MILP [202, 203]. Lyapunov optimisation is used in [204] and a constrained Markov decision process (MDP) is used in [205]. [206] uses an agent-based graph search algorithm and [207, 208] use heuristic methods. The end goal of the works reviewed can be broadly divided into three areas, based on the objective function to be optimised: the maximisation of RES output, the minimisation of RES curtailment (it is noted that while framed differently, these two points are analogous) or the minimisation of the associated carbon intensity of EV charging.

Works presented in [201], [205] and [204] all act to maximise RES output within the setting of a microgrid or EV charging car park: effectively a single-bus system with both RES generators and EV charging demand. In [201], the authors present a LP approach to minimising the total cost of generation, given a time-varying generation mix with intermittent RES output and a fixed assumption of the number of EVs that make available a certain proportion of their batteries to be used in a bidirectional energy exchange (i.e. V2G). Studies in [205] and [204] both present concepts of a charging station, where EVs must queue to charge. While the methods used are different, the objective functions in both papers are formulated such that they are rewarded with increased use of RES (through there being a lower cost of 'dispatch') and penalised with a longer queue length. Whereas these microgrid/charging car park concepts certainly have their applications, they are not suitable for the study of widespread EV charging as the majority of which is expected to occur at private residencies [15]. [203] uses a MILP approach to simulate the operation of an aggregator who is acting on the behalf of all EVs in a test network to ensure they receive a pre-arranged quantity of energy during the time during which the vehicle is available, subject to network constraints. The aggregator's objective is to minimise their own cost of buying energy for the charging of EVs, which is at a minimum during times of maximum RES output. While this approach is potentially an accurate reflection of how large-scale demand response from EVs may happen, the study in [203] uses overly simplistic assumptions as to when the EVs are plugged in and available, based on a small survey in one town made by the authors. On the contrary, work presented in this chapter uses analysis from a large travel dataset to derive individuals' likely charging behaviour based on the energy requirements of their travel habits.

In [207], the potential reduction in curtailment of wind energy generation is calculated based on a future projection of the Danish energy system in which 8 GW of wind power is installed and there are 500,000 EVs. All EVs in the system are aggregated to form one charging profile, based on a simple assumption relating to typical commuting patterns. By controlling the charging load via a heuristic method that seeks to maximise the utilisation of wind power by charging, it is reported that curtailment can be reduced by 20%. Furthermore, [207] reports that the additional reduction in curtailment from V2G approaches is insignificant, the total reduction from a controlled V2G approach being 21%. In [208], the authors present analysis of the ability to reduce wind curtailment of six separate heuristic-based strategies for controlled EV charging, reporting a reduction of wind curtailment between 13% and 51% depending on the type of approach used. All strategies are tested on the concept of a 'nationwide battery' active during the assumed charging period of 23:00-07:00, i.e. an aggregation of all the hypothetical EVs served by the Dutch energy system – whose energy requirements are based on average travel behaviour in the Dutch national travel survey – into one flexible demand, similarly to the aggregation technique used in [207]. [202] presents an MILP optimisation to minimise the cost of generation given an availability of wind resource (with an associated dispatch cost of zero) and a flexible EV charging demand. While the modelling of EV charging demand in [202] is more sophisticated than in the aforementioned works, based on five different hypothetical archetypes of EV charging relating to the speed at which the vehicles are to be charged, the model uses a single aggregated load accounting for the total annual energy demand from all of Germany's projected 2030 EV fleet, an approach that fails to reflect the diversity in drivers' travel patterns and lacks detail compared with the individual travel diary approach proposed in this chapter.

Works that focus specifically on the carbon intensity of charging are rarer than those that fit into the categories discussed in the preceding two sections. In [209], the authors establish the likely carbon intensity of EV charging given the average intensity (gCO_2/kWh) of the Danish electricity grid, though there is no consideration of the flexibility of EV charging or scheduling of the charging load. [210] presents a similar study based on the GB electricity system. Though the temporal variation in EV charging demand is considered, it is assumed that an increase in demand as a result of EV charging will be met by dispatchable generation and thus the resulting carbon intensity of EV charging is equal to the carbon intensity of the dispatchable energy capacity at a given time. Given the context of the GB system, this is composed of gas and coal plants. In [200], the authors propose a CP method to schedule EV charging to occur at the time of minimum grid carbon intensity. Although it presents an interesting approach, it is suggested that the assumptions regarding vehicles' travel patterns are overly simplistic: it is assumed that all vehicles are present between 17:00 and 08:00 the following morning, based on the authors' interpretation of a typical working day. Furthermore, the focus on plug-in hybrid EVs with battery capacities around 5 kWh limits the effect that controlled charging can have, as the total flexibility is less than if pure battery EVs with considerably larger battery capacities – such as in this chapter – are used. Although the primary goal in [202] is to maximise the utilisation of wind power, it also presents the subsequent reduction in carbon intensity of charging as a result of the optimisation; however, the results are based on a constant grid intensity rather than a time series as presented in Section 5.6.

5.2.3 Controlled Charging Techniques in EV Trials

All the approaches discussed in Sections 5.2.1-5.2.2 rely on a set of information that typically would not be available to a network operator or aggregator – particularly, foresight of the arrival and departure times for a fleet of vehicles ahead of real time[1]. In order to be practical, a controlled charging technique must be able to work on the basis of limited information. These practical approaches to controlled charging are represented mainly by those that have been attempted in a small number of EV trials.

The *Ultra Low Carbon Vehicle* demonstrator programme (2009-2012) applied a simple delay to all EV charging, in that the EV could not start drawing power from the grid until 23:30 [211]. While this was shown to reduce the loading on the feeder that would have otherwise resulted from EV charging [212], these simple approaches have been shown to result in a new peak, usually late at night, due to the reduction in diversity of charging load (given that now every EV will start charging at the same time,

[1] Although this foresight will never be possible, it has been shown throughout this thesis that charging patterns are likely to be fairly predictable, based on the small variance within the 95% confidence intervals presented. Therefore, a key part of the future of EV smart charging could involve forecasting the charging requirements of a fleet of vehicles and aggregating their load accordingly. This is further discussed in Section 5.7.1.

regardless of what time it plugged in). For example, early smart charging schemes in Japan based on a delayed charging schedule saw a new peak on distribution systems around midnight as a result [213].

The MEA trial, as introduced in Chapter 4, saw the application of a physical limit on EVs' charging, irrespective of consumer choice. As already discussed in Section 4.5.2, this involved a concept named in the project documentation as 'Esprit', comprising of a 'monitor controller' installed at the local secondary substation which would monitor the current flow on all three phases, and an 'intelligent control box' installed on the customer's premises, essentially a switch that would disconnect the EV and interrupt its charging if the loading conditions at the substation were above a certain threshold. As already mentioned, data released from the project contains information on the total loading as seen by the monitor controllers and the switch state of each intelligent control box (i.e. when charging was interrupted). However, as a given EV is not linked with the substation it is under or the intelligent control box on its charger, it is impossible to quantify how much energy (if any) each car was denied as a result of the charging curtailment.

More recently, focus has been on market-based approaches to smart charging, giving the customer the choice to delay their charging (typically incentivised by financial reward) or be able to charge as and when they want (for an increased cost). For example, in *Electric Nation* [186], the control of charging was based on consumer participation. Every consumer in the trial was given the option of using one of two charging management smartphone apps: GreenFlux [214] and Crowd-Charge [215]. Both apps are based on simple time of use tariffs in which the per unit price of electricity was reduced at off-peak times (i.e. overnight). In GreenFlux, users are by default set to charge only during off-peak hours, but can override this setting via a simple function that requests 'high priority', meaning that the EV will charge irrespective of the per unit price. In Crowd-Charge, the user enters their journey plans until their next charging opportunity and the app works out how much energy must be transferred to the EV, carrying out the charging in the lowest price times. In the first year of the trial for which results are available, 47% of invited participants used GreenFlux at some point, though 32%

of those who used it only used it once. 38% of invited participants used Crowd-Charge at least once during the trial.

5.2.4 Gaps in the Literature

A review of the relevant literature has shown that while this area of research is already well practised, there remain gaps in the collective knowledge. The work presented in this chapter seeks to address these gaps as follows.

Firstly, whereas all of the works reviewed in Section 5.2 use simplistic assumptions regarding the temporal variation in EVs' availability based on impressions of 'typical' driving patterns, this work uses a detailed simulation of the possible plugging in habits of a representative fleet of EVs – which was presented earlier in this thesis in Chapters 2 and 4 – using two different models of charging behaviour to cover the possible spread in charging event frequency and energy requirement.

Secondly, all but one of the works reviewed in Section 5.2.2 assume a constant grid carbon intensity (the exception being [200], though they use a profile for only one day, neglecting considerable day-to-day and seasonal variation resulting from variations in demand and RES output). On the other hand, the investigation of the potential of EVs to support renewables in this work (Section 5.6) uses half-hourly grid intensity data for the GB system from the GB system operator National Grid [216], and half-hourly curtailment data from Whitelee wind farm [217], a large (539 MW) transmission-connected wind farm that is nearby ($<$ 15 km) to the simulated distribution network.

5.3 Formal Optimisation of EV Charging

5.3.1 Overview

In this section, a method for the optimisation of the schedule of charging a fleet of EVs is presented based on a set of network-representative charge diaries derived from travel data as in Chapter 4. The formulation is based on the DC approximation of the optimal power flow problem (DCOPF), a well-known power systems optimisation problem [218] that seeks to find a steady state operating point of a system which minimises the cost of satisfying demand within the constraints of the network. In this work, the optimisation must satisfy all EVs' energy demand between the time at which they plug in and the time at which they depart on their next journey; however, the timing of charge events is flexible (albeit to varying degrees, based on the drivers' travel habits). The proposed formulation of scheduling EV charging is described in Section 5.3.3.

Whereas an ACOPF problem formulation can be thought of as a 'full' model representation of the power system, the DCOPF linearisation makes two key assumptions: firstly, it is assumed that voltage is constant (1 per unit) at all buses. Secondly, it is assumed that reactive power generation and demand are both zero. While the EV charging scheduling optimisation was originally formulated as an ACOPF problem due to the concerns surrounding busbar voltage as discussed at various points in Chapter 4, it was not possible to build the problem for the 1,783 busbar network as used to model the Pollokshields network presented in Section 4.3.2 due to memory constraints on the PC available for this PhD study[2]. This is identified as a significant limitation to this approach, as it is generally acknowledged that ACOPF is required to reliably report results for distribution networks given the significant line impedances and consequential variation in voltage magnitudes and angles [219]. In an attempt to remedy this limitation and examine the impact of optimally scheduled EV charging on busbar voltages and compare it to that arising from uncontrolled and heuristically-scheduled charge events, the solutions of the DCOPF formulation are input into AC load flow calculations (Section 5.4.2).

Section 5.3.2 describes the process by which the derived week-long charging diaries are processed into charging 'flexibility windows' covering one 24 hour period. Section 5.3.3 describes how these charging diaries are scheduled using a DCOPF formulation.

5.3.2 Charging Flexibility Window

The optimisation performed in this study is carried out on the basis of one 24 hour period in 10 minute timesteps, from midday to midday the next day. However, the charging

[2]The PC used was a Dell Inspiron 7050 desktop PC with a 3.6 GHz processor and 8 GB RAM. A decomposition approach to modelling individual parts of the network may allow for the problem to be modelled as an ACOPF formulation. This idea is expanded upon as a suggestion for further work in Section 5.7.1.

schedules produced on the basis of a week-long travel diary as in Chapters 2 and 4 are 7 days long. Therefore, the week-long charge schedules are trimmed accordingly to establish a 'flexibility window' for each charging event that fits into the 24 hour window of the optimisation study. The process by which this is done is illustrated in Figure 5.1.

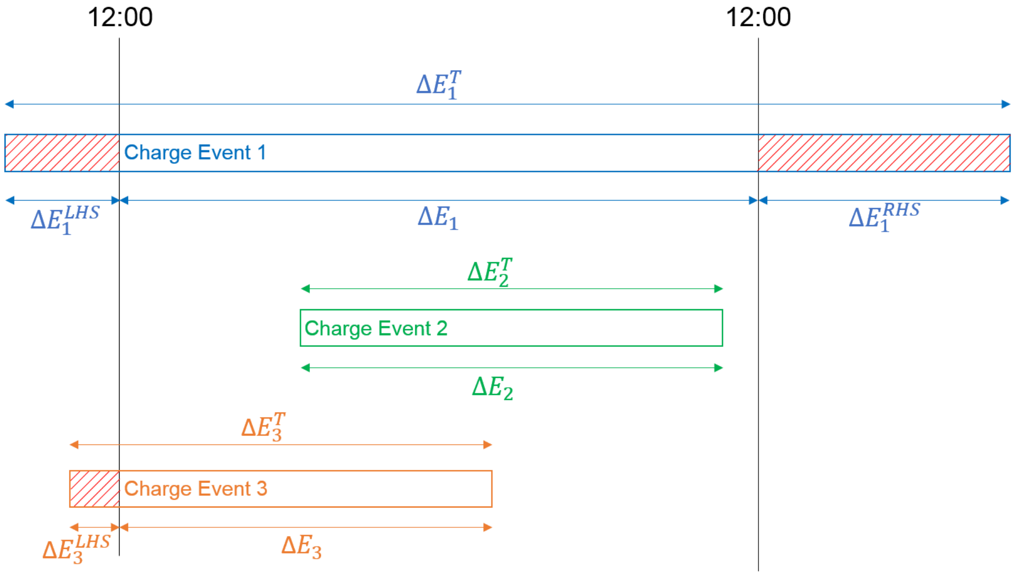

Figure 5.1: Illustrative example of charging flexibility window concept, showing how 7-day charging schedules are trimmed to 1-day charging flexibility windows for optimisation

Upon selection of the 24 hour window within the 7-day long charging schedule, any charge events that are completely outside of the 24 hour window are discarded. Any that overlap the beginning and/or the end of the 24 hour window (e.g. Charge Events 1 and 3 in Figure 5.1) are trimmed accordingly as per (5.1), such that only the energy that would ordinarily have been delivered during the 24 hour window – under an uncontrolled charging schedule – is accounted for.

$$\Delta E_e = \Delta E_e^T - \left(\Delta E_e^{LHS} + \Delta E_e^{RHS}\right) \tag{5.1}$$

where ΔE_e^T is the energy originally delivered during charge event e including in the time outwith the flexibility window, ΔE_e is the energy to be delivered during charge event e within the flexibility window, ΔE_e^{LHS} is the energy to be trimmed from the charge event e overlapping the start of the 24 hour window and ΔE_e^{RHS} is the energy to be trimmed from the charge event e overlapping the end of the 24 hour window.

The energy that is to be trimmed from these charge events is calculated by consideration of a CC-CV charging profile of a lithium-ion battery – the same as in Figure 2.6. The resulting expressions for the calculation of ΔE_e^{LHS} and $\Delta E_e^{'RHS}$ are given in (5.2). For the derivation of these expressions, the reader is referred to Section 2.2.5.

$$\begin{aligned}\Delta E_e^{LHS} =& \frac{\max\{0,(t_e^{\gamma}-t_e^{s})\}}{(t_e^{\gamma}-t_e^{s})}\int_{t_e^s}^{t_e^{\gamma}} P_e^{DC}dt+ \\ & \frac{\max\{0,\left(t_e^{s'}-t_e^{\gamma}\right)\}}{(t_e^{s'}-t_e^{\gamma})}\int_{t_e^{\gamma}}^{t_e^{s'}} P_e^{DC}e^{-\lambda_e t}dt \qquad (5.2a)\\ \Delta E_e^{RHS} =& \frac{\max\{0,(t_e^{\gamma}-t_e^{d})\}}{\left(t_e^{\gamma}-t_d^{s}\right)}\int_{t_d^s}^{t_e^{\gamma}} P_e^{DC}dt+ \\ & \frac{\max\{0,\left(t_e^{d'}-t_e^{\gamma}\right)\}}{(t_e^{d'}-t_e^{\gamma})}\int_{t_e^{\gamma}}^{t_e^{min}} P_e^{DC}e^{-\lambda_e t}dt \qquad (5.2b)\end{aligned}$$

where t_e^s is the original start time of the charge event e, $t_e^{s'}$ is the adjusted start time of the charge event e (i.e. the start of the 24 hour window), t_e^d is the original departure time of charge event e, $t_e^{d'}$ is the adjusted departure time of the parking event following trip e (i.e. the end of the 24 hour window). t_e^{γ} is the time at which the EV's SoC reaches γ (taken as 0.8 as in previous analysis presented in this thesis), at which point the charging profile transitions from the CC to the CV region. As before, λ_e is the decay constant of the CV region during charge event e and P_e^{DC} is the rated DC charging power (equal to the AC charging power demanded from the network multiplied by a one-way efficiency – 88% in accordance with analysis in Chapters 2-4). t_e^{min} is the minimum of t_e^d and t_e^{∞} (5.3).

$$t_e^{min} = \min\{t_e^{\infty}, t_e^{d}\} \qquad (5.3)$$

5.3.3 EV Scheduling

This section describes how the EVs' charging requirements are scheduled within their flexibility windows as described in the preceding section.

Power Flow

The power balance equation is given as (5.4), $\forall\ b \in \mathcal{B}, \tau \in \mathcal{T}$:

$$\sum_{g \in \mathcal{G}} p^G_{g,\tau} = \sum_{e \in \mathcal{E}} p^E_{e,\tau} + \sum_{d \in \mathcal{D}} p^D_{d,\tau} + \sum_{l \in \mathcal{L}} p^L_{l,\tau} \tag{5.4}$$

where $\mathcal{B}$ is the set of busbars in the network, $\mathcal{T}$ is the time horizon (the set of 10 minute timesteps indexed by τ), $\mathcal{E}$ is the set of charge events across all EVs in the fleet, $\mathcal{D}$ is the set of domestic demands (i.e. one per household) and $\mathcal{L}$ is the set of lines in the network. $p^G_{g,t}$ is the active power contribution from the grid supply point g in the time period $[\tau, \tau+1]$, $p^E_{e,\tau}$ is the active power drawn by an EV in charge event e to charge its battery in the time period $[\tau, \tau+1]$, $p^D_{d,\tau}$ is the active power drawn by domestic demand d in the time period $[\tau, \tau+1]$ and $p^L_{l,\tau}$ is the active power flow on line l in the time period $[\tau, \tau+1]$.

The power flow equations are given as (5.5a-5.5b), $\forall\ l \in \mathcal{L}, \tau \in \mathcal{T}$:

$$p^L_{l,\tau} = -B_l \left(\delta_{b,\tau} - \delta_{b',\tau}\right) \tag{5.5a}$$

$$-S^{DC}_l \le p^L_{l,\tau} \le S^{DC}_l \tag{5.5b}$$

where B_l and S^{DC}_l are the susceptance and rating respectively of line l, and $\delta_{b,\tau}$ and $\delta_{b',\tau}$ are the voltage angles at b and b', denoting the busbars at either end of line l, in the time period $[\tau, \tau+1]$.

EV Charging Model

The energy storage content of an EV $E_{e,\tau}$ during charge event e at timestep τ is related to that in the previous timestep and the energy gained in the time period $\Delta\tau = [\tau, \tau+1]$

(10 minutes) by (5.6).

$$E_{e,\tau} = p^{E}_{e,\tau}\Delta\tau + E_{e,\tau-1} \tag{5.6}$$

The power drawn by an EV is constrained by the same CC-CV charging profile as used several times already in this thesis (e.g. Figure 2.6). The charging power constraint is stated formally in (5.7).

$$p^{E}_{e,\tau} \leq \begin{cases} P^{DC}_{e}, & S_{e,\tau} \leq \gamma \\ \left(\dfrac{1 - S_{e,\tau}}{1-\gamma}\right) P^{DC}_{e}, & S_{e,\tau} > \gamma \end{cases} \tag{5.7}$$

where the SoC of an EV in charge event e at timestep τ, $S_{e,\tau}$, is calculated by (5.8) and constrained between the SoC on arrival and the SoC on departure (5.9); given by the vehicle's energy storage content as a fraction of the battery capacity C_e .

$$S_{e,\tau} = \frac{E_{e,\tau}}{C_e} \tag{5.8}$$

$$\frac{E^s_e}{C_e} \leq S_{e,\tau} \leq \frac{E^d_e}{C_e} \tag{5.9}$$

where E^s_e and E^d_e are the energy storage contents of the vehicle at the start and end of the flexibility window defining charge event e.

Objective Function

The goal of the optimisation is to minimise the objective function (5.10): the sum of the cost of CO_2 emissions plus the sum of the cost of not meeting any demand, both domestic and from EV charging. Although the values of lost domestic load and lost transport energy are likely to be different, in this work the values of lost load V^D_d and V^E_e are both taken as £17,000/MWh[3] in accordance with the value published by London

[3]In reality, it would be reasonable to expect that these values would be quite different, due to the variation in consumers' willingness to pay for domestic electricity (which would vary depending on which appliance was being used, when it was being used and, of course, by whom) and transport, which would also be expected to vary significantly in time depending on when any period of lost load would occur relative to tasks that would be deemed important to the consumer. However, as in this

Economics for the Department of Energy & Climate Change and Ofgem [80]. The cost of emissions is given by the total emissions in kg multiplied by a cost per kg Γ – in this work, the UK carbon floor price (2018-2021) of £18/tonne (£0.018/kg) [220] is used.

$$\min \sum_{\tau \in \mathcal{T}} \left(\underbrace{\sum_{g \in \mathcal{G}} \Gamma c^G_{g,\tau} p^G_{g,\tau}}_{Cost of CO_2 emissions} + \underbrace{\sum_{d \in \mathcal{D}} V^D_d \left(P^D_{d,\tau} - p^D_{d,\tau} \right)}_{Cost of shedding domestic load} + \underbrace{\sum_{i \in \mathcal{I}} V^E_e \left(P^E_{e,\tau} - p^E_{e,\tau} \right)}_{Cost of shedding EV demand} \right) \Delta\tau \tag{5.10}$$

where $c^G_{g,\tau}$ is the grid carbon intensity of grid supply point g during the time period $[\tau, \tau+1]$. $P^D_{d,\tau}$ is the active power demand from domestic demand d during the time period $[\tau, \tau+1]$; $P^E_{e,\tau}$ is the active power demand from EV charging event e during the time period $[\tau, \tau+1]$.

The objective function in (5.10) is minimised subject to the constraints in (5.4-5.9). The problem is solved using the CPLEX solver using OATS [221] optimisation software.

In this work it is assumed that the marginal increase of EV charging will not lead to an increase in carbon intensity of the grid (through dispatch of fossil fuelled generation). While this assumption could be considered reasonable for the small fleet of EVs considered relative to the carbon intensity of the GB grid, this would change if the modelling were extended nationwide. This is further discussed in Section 5.7.

study the network was able to serve all load within thermal limits under the DC OPF assumptions, any relative difference in these values would have zero effect on the results presented.

5.4 Optimal Scheduling of Electric Vehicle Charging for 'Valley Filling' of Distribution System Load Profile

In this section, the formulation presented in Section 5.3 is applied to the same Pollokshields network and set of EV parameters as presented in Section 4.7 – recall that this was: EVs had battery capacities sampled from a symmetrical distribution (Figure 4.39); all EVs had 'high' charging power corresponding to 7.4 kW at home; all EVs had access to charging at home; workplace charging access was assigned based on results from the NTS; public charging access was assigned to 50% of vehicles at random. This analysis was carried out for 10 MC trials on the Pollokshields network, all of which are brought forward to this section. The week-long charging schedules as derived for analysis in Section 4.7 were trimmed to one 24 hour window as per the method in Section 5.3.2. For this analysis, the time period from 12:00 on Tuesday to 12:00 on Wednesday was chosen as to minimise the influence of the assignment of a random SoC to each vehicle at the start of their travel diary. In comparison to the analysis presented in Chapter 4 (in which the network loading was shown for a 48 hour period), the optimisation windows in this chapter are 24 hours in duration. This was decided as a result of a 24 hour period clearly being a 'repeating unit', and the consequential reduction in computational burden from optimising charging over a shorter time period.

The goal of the optimisation here is known as 'valley filling' [222]; by scheduling EV charging such that overall network loading is kept to a minimum, the goal of serving all vehicles with the amount of energy they need while operating the network within its limits can be sought. As already mentioned, the network could not be formulated into an ACOPF problem because of its sheer size – therefore, the DCOPF formulation was used to derive the EV charging schedule that minimises the total network loading, and the results of that are then input into an AC load flow with the same power factor as before (0.98 for EV charging [183], 0.95 for domestic demand [184] – both lagging).

5.4.1 Method

To find the schedule that minimises the total network loading for all timesteps, line losses (as a proportion of flow on each line) are introduced into the DCOPF formulation as an additional constraint. Then, as the minimisation of the objective function (5.10) is sought, this will involve the minimisation of flows on all lines in the network.

In effect, line losses are used as a proxy to force the optimisation into finding the minimum network loading; accurate reporting of network losses is not a priority. Losses are formulated as a constraint in (5.11); the absolute difference between the real power flowing from bus b to bus b' and the reverse flow from bus b' to b is equal to a constant loss factor L_l on line l.

$$\left| \frac{|p^L_{bb',\tau}| - \left|p^L_{b'b,\tau}\right|}{p^L_{bb',\tau}} \right| = L_l \tag{5.11}$$

To approximate the loss factor L_l for each line $l \in \mathcal{L}$, the uncontrolled charging schedules are run through an AC load flow calculation to generate losses on each line. As these losses will change with the network loading, an average value over the complete 24 hour time period is taken for each line. This is illustrated in Figure 5.2, which shows a scatter plot of the mean, minimum and maximum loss factors over 144 AC load flow simulations, one for each 10 minute timestep in the 24 hour period. Note that these loss factors appear small compared to the overall distribution network losses reported by Ofgem in [223]; the lines in the network model are broken up to allow the modelling of individual joints and customers endpoints (such that the average line length in the Pollokshields network is 16.2 m). The loss factor L_l for each line l is then set to the mean loss factor for the corresponding line l.

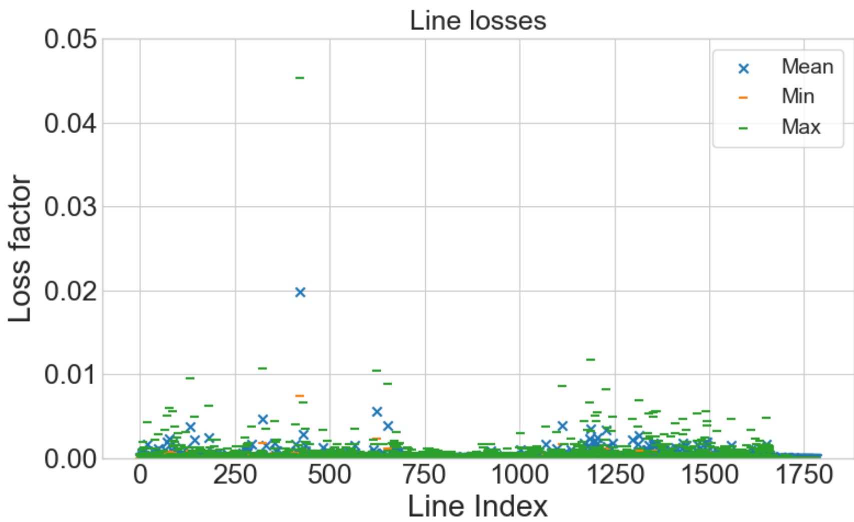

Figure 5.2: Mean, maximum and minimum loss factors for all lines in Pollokshields network, uncontrolled EV charging (100% penetration) – 144 AC load flow simulations covering 24 hour period in 10 minute timesteps

The constraint given in (5.11) is added to the former constraints (5.4-5.9) and the objective function in (5.10) is minimised as before, $\forall\ \tau \in \mathcal{T}$. Note that due to the introduction of two terms for active power flow on each line ($p^L_{bb',\tau}$ and $p^L_{b'b,\tau}$), the term $p^L_{l,\tau}$ as used in (5.5a-5.5b) is computed as the average of the former two (5.12).

$$p^L_{l,\tau} = \frac{1}{2}\left(p^L_{bb',\tau} - p^L_{b'b,\tau}\right) \tag{5.12}$$

For this analysis, the grid carbon intensity $c^G_{g,\tau}$ is kept constant at the average GB value (221 gCO_2/kWh; see analysis in Section 5.6.1 for details): therefore, the result of the optimisation is that it seeks to schedule EV charging such that overall network loading is a minimum.

5.4.2 Results

Figure 5.3 shows the network loading from EV charging only, both for uncontrolled charging and the results of AC load flow simulations of the solutions to the valley-filling optimisation described above. Figure 5.4 shows the total network loading (domestic plus EV charging) for the same cases. Note that in both figures, as with other load profiles presented in this thesis, the shaded region shows the 95% confidence interval of results across all trials.

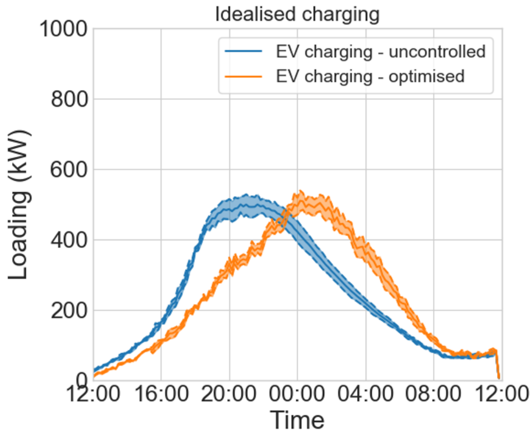

Figure 5.3: Network loading from EV charging for Pollokshields network, uncontrolled and valley-filling optimised schedule: idealised (left) and routine charging (right)

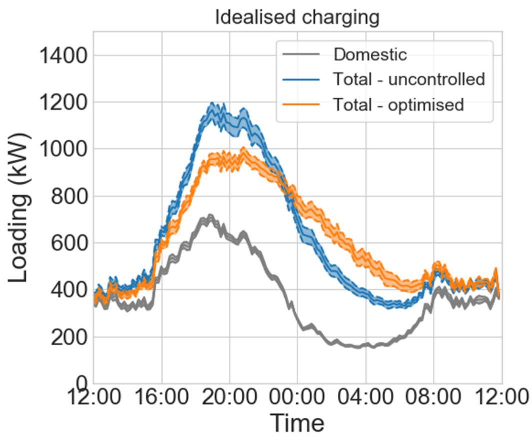

Figure 5.4: Total network loading for Pollokshields network, uncontrolled and valley-filling optimised schedule: idealised (left) and routine charging (right)

By shifting the EV charging demand later into the night (Figure 5.3), the overall network peak can be reduced substantially (Figure 5.4) – the average reduction in peak demand was 15.7% for the idealised charging scenario and 27.6% for the routine charging scenario.

While the point of minimum domestic demand is shown to be around 04:00, the point of maximum EV charging in the valley-filling case is shown to be around 00:00-

01:00. This is because the vehicles' charging is constrained in how much energy must be delivered before they leave (which for many vehicles occurs within the period 07:00-10:00, as shown in Figure 1.6) and the maximum power that can be delivered to the vehicle (5.7).

The energy requirement, and especially peak power, were shown to be greater for the routine charging case as was found in Chapter 4. However, the ability to shift this energy into late into the night is shown to be comparatively greater for the routine case; this is likely because while there are more vehicles charging, their individual energy requirements are smaller and hence charging events are more flexible. The resulting peak demand of the optimised charging is not as different between the two cases as for their uncontrolled peak demands: for the idealised case, the network would see an average peak (based on optimisation of 10 MC trials) of 982 kW; for the routine case, the network would see an average peak of 1057 kW (an increase of 7.6%). Their average uncontrolled network peaks were 1165 kW and 1460 kW for the idealised and routine cases respectively (the latter representing a 25.3% increase on the former).

Figures 5.5 and 5.6 show scatter graphs of the line loading (as a percentage of capacity) and endpoint voltage (per unit) respectively, both for uncontrolled charging and the results of the optimisation described above. Note that the flat bars on either side of each marker show the upper and lower 95% confidence bounds for each result.

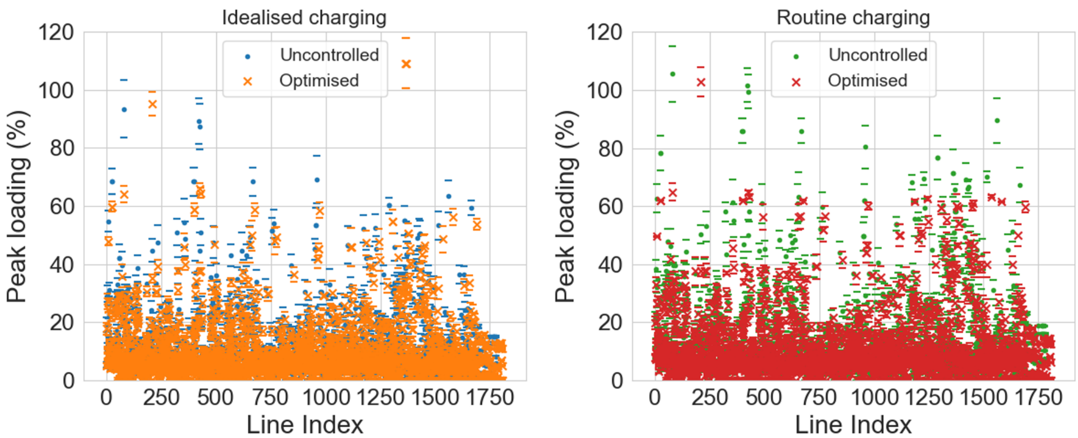

Figure 5.5: Scatter plots of maximum line loading for Pollokshields network, uncontrolled and valley-filling optimised schedule: idealised (left) and routine charging (right)

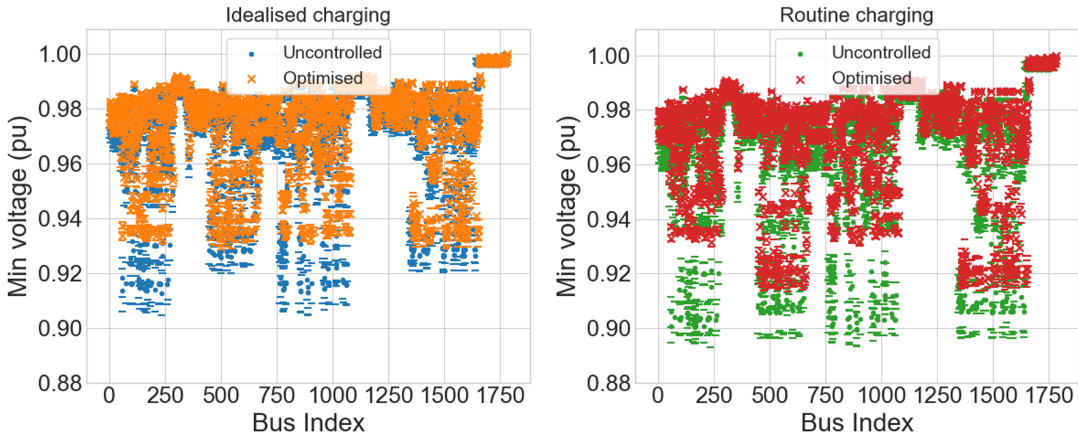

Figure 5.6: Scatter plots of minimum endpoint voltage for Pollokshields network, uncontrolled and valley-filling optimised schedule: idealised (left) and routine charging (right)

Figure 5.5 shows that delivering the optimal schedule of EVs tended to lead to different lines being more heavily loaded than those that were originally. In principle, the optimised solution will have no lines overloaded. However, it was based on a simple DC approximation of line flows, and the results from AC load flow simulation of the optimised schedule show that some lines are overloaded some of the time due to reactive power transfers. This could be remedied by reducing the thermal limits on lines in the network as part of the DCOPF formulation.

Figure 5.6 shows that the optimal schedule of EVs has the potential to increase the minimum endpoint voltages across the network: as with the overall network loading in Figure 5.4, the proportional increase is shown to be greater for the routine charging case than for the idealised. Despite these increases, it is shown that the minimum endpoint voltages for this network are below statutory GB limits (+10/-6%) [185] even for the optimally scheduled EV charging for both the idealised and routine charging cases. Table 5.1 presents a series of summary metrics on the violation of voltage levels by the uncontrolled and optimised charging schedules, in terms of i) the proportion of time for which the limits were violated, ii) the minimum voltage that was found and iii) the average breach magnitude. All values in Table 5.1 are reported as mean values of the 10 trials conducted.

Table 5.1: Summary metrics for violation of voltage limits in Pollokshields network for uncontrolled and optimised charging; idealised and routine charging cases

	IDEALISED		**ROUTINE**	
	Uncontrolled	**Optimised**	**Uncontrolled**	**Optimised**
Proportion of time voltages in violation (%)	20.3	17.8	25.3	25.2
Minimum voltage (pu)	0.910	0.929	0.893	0.915
Average breach magnitude (pu)	0.0069	0.0023	0.0114	0.0049

It is noted that the proportion of time for which the voltages are in violation is remarkably similar for the optimised case as it is for the uncontrolled case for routine charging behaviour. Whilst this is an interesting part of the result, likely due to a sideways shift of charging demand later into the night due to the decrease in domestic activity and hence electrical demand, the average breach magnitude is shown to have reduced significantly.

The fact that even after the optimisation of charging schedules the network is still operating outwith voltage limits for a significant proportion of the time is an important result, as it can be concluded that 100% penetration of EVs cannot be accommodated within the Pollokshields network (and therefore, likely many other residentially-dominated networks in better-off areas in GB) if all of their home charging requirement is to be met and the voltage at the LV bus of the primary substation is 1 pu[4].

Although the optimal scheduling of EV charging has not been successful at maintaining the network within voltage limits, the potential reduction in network loading is a result of the ‘best case’ scheduling, assuming that a central controller not only has access to every vehicle’s battery size, current SoC, duration of stay but a perfect foresight of the arrival of future vehicles. Clearly, this scenario is not a realistic one – though accurate forecasting of the arrival of future vehicles and their energy demands could play an important part: this is expanded up on in Section 5.7.1. Though the context of how optimal scheduling of EV charging given a forecast of future vehicle arrivals and their likely travel habits is discussed in Section 5.7, this remains a formidable challenge.

[4]The DNO may choose to operate the network with the primary substation at a higher voltage level than this (this transformer has an OLTC with a maximum tap setting of 5%). However, this relies on reasonable forecasts of both EV charging demand and the output of any distributed generation in the network, such as rooftop solar PV.

In the next section, a set of heuristics are presented which can schedule EV charging on a series of rules without knowledge of the rate of arrivals of vehicles or their energy requirements.

5.5 Low Information Heuristic Methods for Scheduling Electric Vehicle Charging

Heuristic-based charging scheduling methods have been used in real EV trials as discussed in Section 5.2.3 to varying levels of success. The key difference between them and the optimal scheduling approach presented in the preceding section is that whereas in the optimal scheduling approach, all vehicles' energy requirement will be met (at least if the problem is feasible), there is no such guarantee for heuristic-based methods.

This section is concerned with the scheduling of EV charging demand by heuristic-based methods that could be carried out using the information that would be ascertainable from 'smart' EV charge points (the arrival times of the vehicles and their SoC). The heuristic scheduling methods are based on three approaches: i) applying a delay to all charge events that plug in within a peak period; ii) applying a queue system based on 'first come first served' (FCFS); iii) applying a queue system based on 'lowest range first served' (LRFS). These heuristic methods are compared to the optimally scheduled charge events in terms of the impact seen by the network (in terms of thermal loading and endpoint voltage) and the impact seen by the drivers (in terms of the impact on their future travel requirements).

5.5.1 Methods

Simple Delayed Charging

The simple delay heuristic acts to delay all charge events that attempt to begin between the hours of 16:00-00:00. At 00:00, all of the charge events that would have begun in this period are suddenly brought online. Their initial state of charge, maximum charging rate and departure time remain unchanged.

As already discussed in Section 5.2, this method of delaying charge events was used in the *Ultra Low Carbon Vehicle* demonstrator programme [211] and was shown to reduce the loading on the feeder from EV charging [212]. However, it was shown that as EV penetration increases, these control schemes can result in a new peak on distribution systems [213].

First Come First Served Queued Charging

The First Come First Served (FCFS) method attempts to solve the problem of a new peak occurring as a result of the simple delay heuristic. Within the peak domestic load hours 16:00-18:00, all charge events that would have began are delayed until at least 18:00. When each vehicle attempts to begin charging, it is given a place in a virtual queue; this queue sets the order in which the charging events will be brought online after 18:00. The spacing s between cars being brought online (minutes) is inversely proportional to the number of cars N_c that attempted charge events in the peak period, such that all cars are charging before 00:00 (360 being the number of minutes between 18:00 and 00:00).

$$s = 360/N_c \tag{5.13}$$

Lowest Range First Served Queued Charging

The Lowest Range First Served (LRFS) method is similar to the FCFS method, except that the vehicles are now brought online in the order of smallest to largest remaining range (km), based on their energy storage content at the time of plugging in and the combined consumption value of their energy consumption: that is, for batteries of the same size, the vehicle with the lowest state of charge would have its charging started first. The aim of this method is to minimise the impact of this form of managed charging on individuals' upcoming travel habits.

5.5.2 Results

Network Impact

Figure 5.7 shows the network loading from EV charging only, both for uncontrolled charging and the results of all three heuristic methods described in Section 5.5.1. Figure 5.8 shows the total network loading for the same cases. As before, the shaded region represents the 95% confidence interval of reported results.

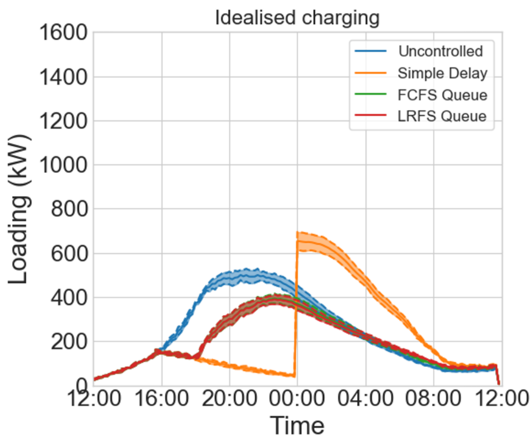

Figure 5.7: Network loading from EV charging for Pollokshields network, uncontrolled and heuristic charging schedule methods: idealised (left) and routine charging (right)

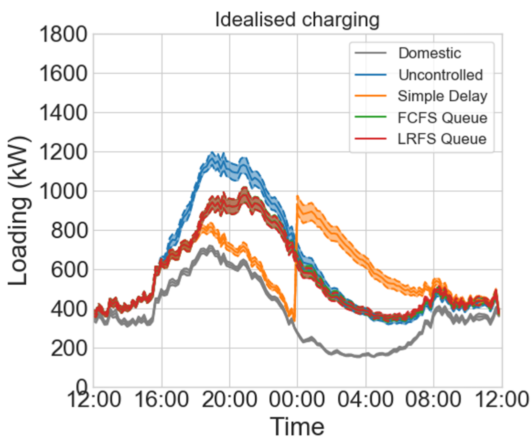

Figure 5.8: Total network loading for Pollokshields network, uncontrolled and heuristic charging schedule methods: idealised (left) and routine charging (right)

Figure 5.7 shows how the simple heuristics altered the total network demand arising from EV charging. Although the FCFS and LRFS queue delays were able to significantly reduce peak demand, the simple delay heuristic increased the EV charging demand due to a loss in diversity. However, this new peak at 00:00 is no longer concurrent with the existing network peak, and this means that at least for the idealised charging case, the overall network peak is reduced from the simple delay (Figure 5.8). For the routine charging case, the new peak far outstrips the old one due to the greater number of vehicles attempting to plug in during the peak period. Aside from the size of the peak caused by the simple delay heuristic, the very steep ramp rate of power demand resulting from the sudden bringing online of all the delayed charge events would present a significant challenge to the power system.

A noteworthy result from Figures 5.7 and 5.8 is that, for the idealised charging case, the traces of the FCFS and LRFS queue heuristics are indistinguishable from one another right up until the end of the night. This is likely due to the generally larger energy requirement of vehicles in the idealised case – whether they are queued by order of arrival of by lowest range first, their charging power tends towards the maximum possible for a large part of the night. It is clear that for the routine charging case, there is a clearer difference (though they are still quite similar): it is expected that this is because the smaller energy requirement means that a significant proportion of those charging events brought online will very quickly reach SoCs above γ (in this case, 0.8) and therefore their charging power (and contribution to total network loading) will reduce.

Figures 5.9 and 5.10 show scatter graphs of the line loading (as a percentage of capacity) and endpoint voltage (per unit) respectively, both for uncontrolled charging and the results of all three heuristic methods described in Section 5.5.1. As before, the flat bars represent the 95% confidence intervals of results across the MC trials.

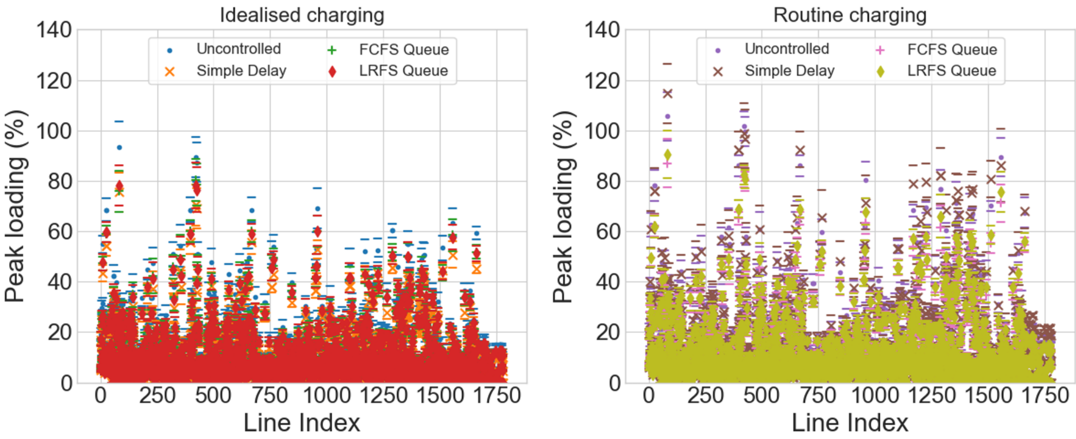

Figure 5.9: Scatter plots of maximum line loading for Pollokshields network, uncontrolled and heuristic charging schedule methods: idealised (left) and routine charging (right)

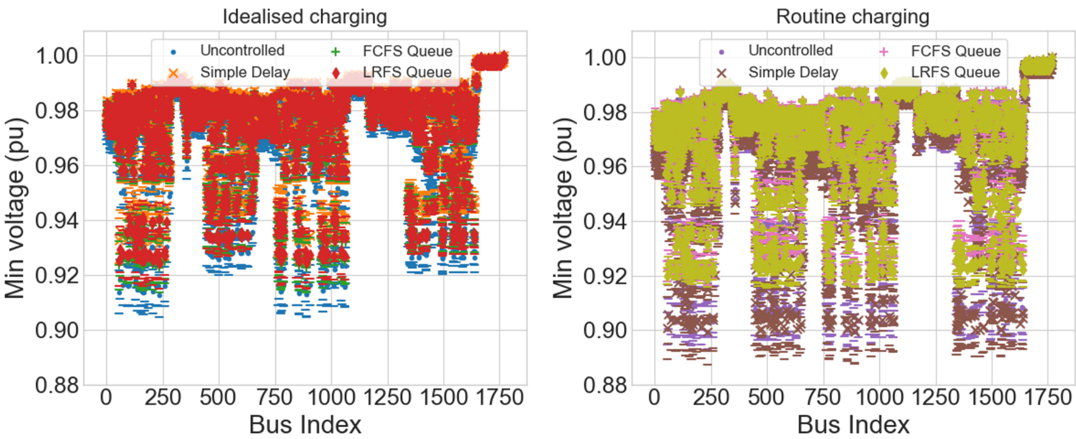

Figure 5.10: Scatter plots of minimum endpoint voltage for Pollokshields network, uncontrolled and heuristic charging schedule methods: idealised (left) and routine charging (right)

As was seen in Figure 5.8, Figures 5.9 and 5.10 show that for the routine charging case, the network is brought under increased stress from the simple delay heuristic. The network is relieved of stress for both charging scenarios under the FCFS and LRFS queue heuristics. However, as before it is shown that even under the FCFS and LRFS queue heuristics, the endpoint voltages remain outwith GB statutory limits for both idealised and routine charging cases.

As for the formal optimisation presented in Table 5.1, Table 5.2 presents the same series of summary metrics – as average values across the 10 trials – on the violation of voltage levels by the uncontrolled and optimised charging schedules, in terms of i) the proportion of time for which the limits were violated, ii) the minimum voltage that was found and iii) the average breach magnitude.

Table 5.2: Summary metrics for violation of voltage limits in Pollokshields network for uncontrolled and optimised charging; idealised and routine charging cases

	IDEALISED				**ROUTINE**			
	Unc.	**Simple**	**FCFS**	**LRFS**	**Unc.**	**Simple**	**FCFS**	**LRFS**
Proportion of time voltages in violation (%)	20.3	6.39	12.15	11.67	25.3	10.42	17.22	18.47
Minimum voltage (pu)	0.910	0.929	0.919	0.920	0.893	0.885	0.916	0.913
Average breach magnitude (pu)	0.0069	0.0035	0.0053	0.0051	0.0114	0.0115	0.0058	0.0070

By comparing the values in Tables 5.1 and 5.2, it is shown that the the FCFS and LRFS queue heuristics perform similarly to the formal optimisation, in terms of the minimum voltage in the network and the average breach magnitude. Although the simple delay method is the most effective at reducing the proportion of time for which the voltages are outside limits (due to the sharp peak), the minimum voltage seen is lower than the uncontrolled minimum for the routine charging case. However, as already mentioned, there is no guarantee in the heuristic-based methods that the energy demanded by each EV will be met during their charging flexibility window. In the next subsection, the effect of these heuristics on the travel demands of the EV drivers is analysed to quantify the potential forfeit associated with using these methods relative to a formal optimisation.

Travel Impact

Figure 5.11 shows the proportion of EVs of those that plugged in for whom the energy delivered was less than that which would have been delivered by an uncontrolled charging event. Figure 5.12 shows the proportion of EVs of those that plugged in for whom the energy delivered was not sufficient to enable them to reach their next charging opportunity (with at least 25 km remaining range) without having to charge en route (and therefore disrupt their journey).

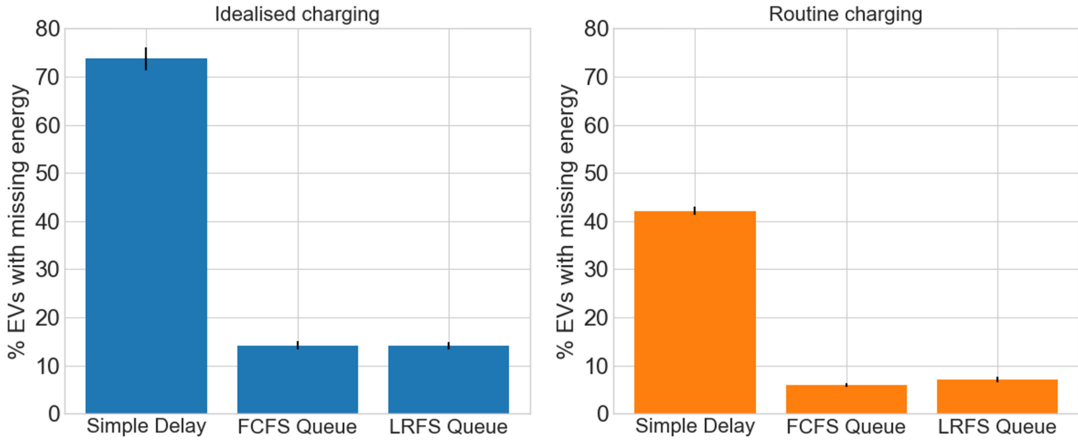

Figure 5.11: Bar chart showing proportion of EVs that plugged in to charge that received a smaller amount of energy than they would have done otherwise following a heuristic charging method being applied – idealised (left) and routine charging (right)

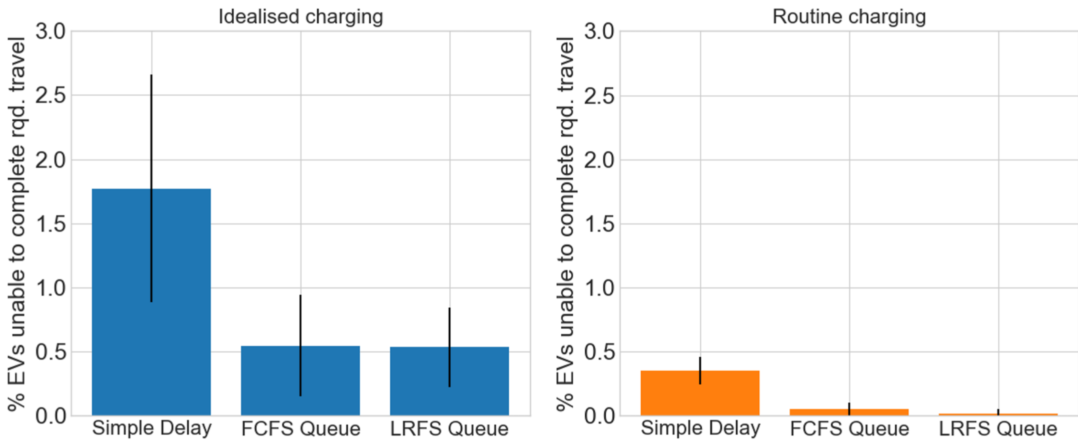

Figure 5.12: Bar chart showing proportion of EVs that plugged in to charge that were rendered unable to reach their next charging opportunity following a heuristic charging method being applied – idealised (left) and routine charging (right)

Figure 5.11 shows that whereas the simple delay results in a considerable proportion of EVs (up to 75% in the idealised case) having some energy 'missing', the FCFS and LRFS queue are better at ensuring that the majority of vehicles ($\sim$ 85% in the idealised case and $\sim 92\%$ in the routine case) were able to carry out their charge events and receive the same amount of energy that they would have done from uncontrolled charging.

Figure 5.12 shows that the proportion of vehicles whose travel plans are affected by these heuristics is significantly lower. If vehicles charge routinely, a diminishingly small proportion of vehicles have their travel plans affected by these charging strategies. This is likely because the SoC on plugin tends to be higher for these vehicles, as the distance travelled since their last charging event tends to be lower. While an average of 0.35% of vehicles that plugged in had to charge before their next charging opportunity under the simple delay heuristic, this was reduced to 0.054% and 0.017% for the FCFS and LRFS queue heuristics respectively.

A shortfall of this analysis is that it does not consider the 'knock-on effect' of these charging management strategies; i.e. if a driver is faced with having their charging managed for subsequent nights while parked, the probability of them having to stop to charge en route may increase. This is recommended as a piece of further work from this study, and expanded upon in Section 5.7.1.

5.6 Optimal Scheduling of Electric Vehicle Charging to Enable the Further Decarbonisation of the Energy System

This section presents an application of the optimisation formulation presented in Section 5.3 to investigate the potential for EVs to i) reduce the CO_2 emissions associated with their driving by selectively charging when grid carbon intensity (gCO_2/kWh) is low and ii) assist in further 'greening' the grid by using excess wind generation in times when it would otherwise be curtailed due to lack of local demand and transmission capacity to transport the power elsewhere.

5.6.1 Minimising the Carbon Emissions Associated with EV Charging

This section presents an investigation of the potential for a fleet of EVs to minimise the CO_2 emissions associated with their charging, by selectively charging when grid intensity is low and taking advantage of surplus low-carbon generation from a nearby wind farm, subject to the constraints of a section of the Pollokshields distribution network.

Distribution Network Model

The network used in this section represents a part of the Pollokshields network, consisting of a secondary (11/0.4 kV) substation and three 0.4 kV distribution feeders. The network serves 157 households, spread amongst 47 endpoints (i.e. there are some address points that are apartment blocks with multiple households). As before, it is assumed that the different households are equally divided among the three phases and that those phases are balanced. Figure 5.13 shows a plot of the network topology with the location of the secondary substation highlighted (left) and a rendered 3D image of the area in question (right) – imagery from Google Maps [224].

Figure 5.13: Glasgow Southside network used for instantiation of EV fleet (left) and rendered 3D image of area in question (right)

Carbon Intensity Data

Half-hourly carbon intensity data for the GB grid was obtained through the National Grid Electricity System Operator (ESO) carbon intensity application programming interface (API) [216]. Table 5.3 shows the assumed carbon intensity of each generation type, which is used by National Grid ESO to calculate the carbon intensity based on the generation mix per half-hour settlement period. The period used for this work is 12 months from 1 June 2018 to 31 May 2019 – the most recent 12 month period available when this study was carried out.

Table 5.3: GB grid carbon intensity and generation by fuel type from 1 June 2018 to 31 May 2019, source: National Grid ESO, Elexon

Fuel Type	**Carbon Intensity (gCO_2/kWh)**	**Generation (TWh)**	**Generation (%)**
Gas - Combined Cycle	394	115.3	41.0
Gas - Open Cycle	651	0.01	0.0
Wind	0	41.08	14.6
Hydro	0	5.3	1.9
Coal	937	9.7	3.4
Nuclear	0	57.1	20.3
Dutch Imports	474	6.7	2.4
French Imports	53	12.8	4.6
Irish Imports	458	1.8	0.7
Solar	0	11.5	4.1
Biomass	120	17.1	6.1
Other	300	2.8	1.0
Total	-	281	-

Based on the data presented in Table 5.3, the average GB grid carbon intensity for 1 June 2018 to 31 May 2019 is estimated at 221 gCO_2/kWh. This figure continues the significant reduction in carbon intensity from 469 g/kWh (combustion only) for the UK in 2013 [225], to under 350 g/kWh in 2015 [226]. To meet UK government targets for decarbonisation, these trends must be continued to be in line with the CCC target of below 200g/kWh for 2020 to below 100 g/kWh in 2030 [227].

In this study, an MC-based method is used to conduct the analysis for 100 trials (as the network is smaller, more variation is expected between trials). Each trial, the charging schedules of a different fleet of EVs as instantiated in the network model are optimised for the minimum carbon intensity, given a different 24 hour period of carbon intensity data. The grid carbon intensity of the 100 24 hour periods as used in this study were selected randomly from the period 1 June 2018 to 31 May 2019 (Figure 5.14).

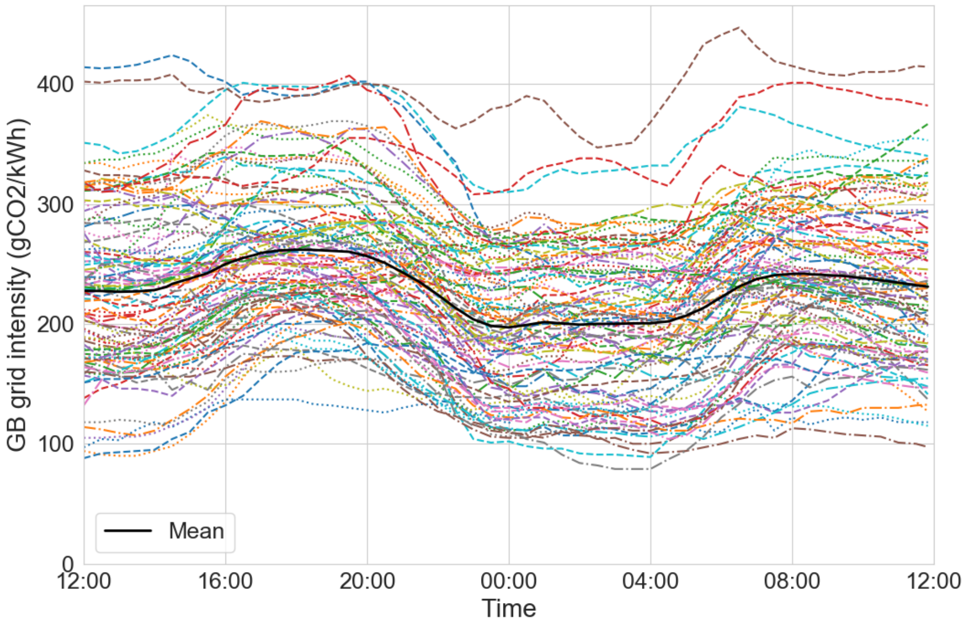

Figure 5.14: Half-hourly GB grid carbon intensity (gCO_2/kWh) for 100 randomly selected weekdays in the period 1 June 2018 to 31 May 2019

Figure 5.14 shows significant variation in the grid carbon intensity, ranging from 79 gCO_2/kWh at 04:00 on 23 August 2018 to 447 gCO_2/kWh at 07:00 on 23 January 2019. The mean carbon intensity value at each settlement period is shown to be lower in the night-time (22:00-05:00) than in the day. This is an important result; as was found by analysis presented in Chapter 4, EV charging is generally more likely to be done overnight as people are parked at home.

Wind Curtailment Data

Whitelee wind farm is a 215-turbine, 539 MW onshore wind farm near Eaglesham, approximately 15 km to the south of Glasgow. Wind power in Scotland needs to be curtailed if exports from Scotland exceed the capacity of the B6 boundary – the transmission corridor between Scotland (which usually runs a generation surplus) and England (which usually runs a deficit). It is found from review of Balancing Mechanism data [217] that output from Whitelee is one of the two wind farms often chosen by the

ESO to be curtailed. During these times, the wind farm's output is curtailed at an average cost of £70/MWh (based on the average bid price from [217]). Whitelee represented 11.5% of total Scottish wind farm curtailment from the 1 of June 2018 to the 31 of May 2018, second only to the neighbouring Clyde wind farm, which made up 13%. The wind farm and test network are in close proximity; electrically, they are connected by 275 and 132 kV transmission lines. It is assumed that these have sufficient capacity headroom to allow increased demand from Glasgow (as a result of EV charging) to be balanced by curtailed wind energy from Whitelee (Figure 5.15, adapted from [228]). Therefore, for any period in the 100 days represented in Figure 5.14 in which there was also curtailment at Whitelee, the grid carbon intensity for that period was set to 0 gCO_2/kWh – in accordance with the methodology used in [216].

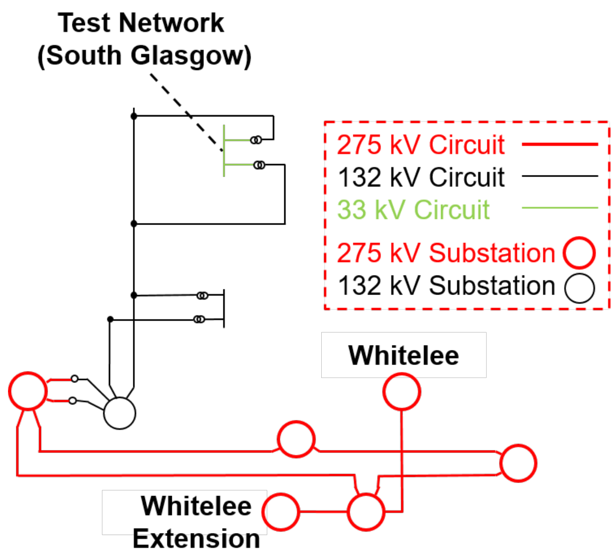

Figure 5.15: Network diagram from Whitelee wind farm to the test network in the south side of Glasgow, adapted from National Grid. Note: Sections of the electrical line diagram have been removed for clarity

Half-hourly curtailment data for the Whitelee wind farm was obtained from the Elexon Balancing Mechanism Reports [217]. Out of 365 days from 1 June 2018 to 31 May 2019, 112 (31%) saw some curtailment. Figure 5.16 shows the total curtailment by half-hour settlement period (left) and a histogram of daily curtailment volumes (right) for Whitelee wind farm during the time period 1 June 2018 to 31 May 2019.

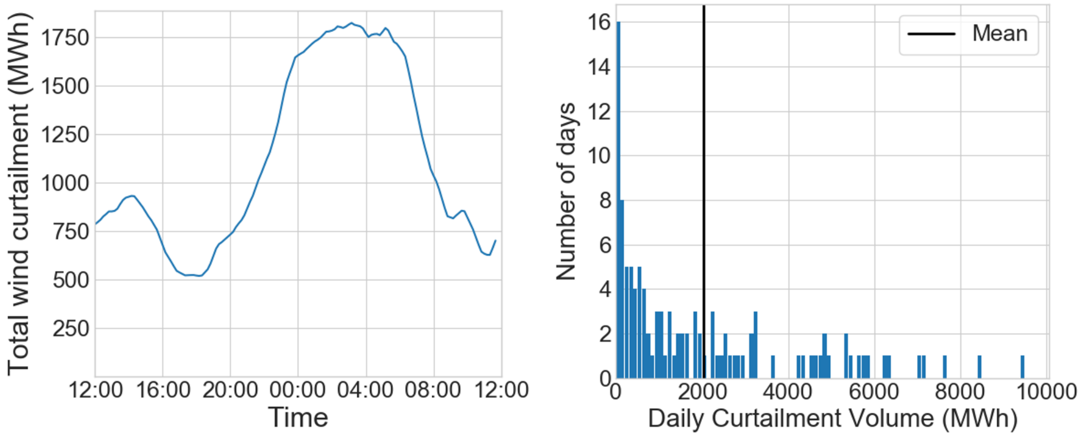

Figure 5.16: Total wind curtailment volumes by half-hour settlement period (left) and histogram of daily wind curtailment volumes (right) of Whitelee wind farm for 112 days where generation was curtailed, 1 June 2018 to 31 May 2019 (bin width = 100 MWh)

Figure 5.16 shows that more generation was curtailed at night than in the afternoon and evening. This is likely due to demand in Scotland being higher in the afternoon/evening than at night. As with the carbon intensity, this is an important result as EV charging is generally more likely to be done overnight. The average daily curtailment out of the 112 days in the year that saw some curtailment was 2030 MWh. The total curtailment of Whitelee wind farm through the year was 227,841 MWh which, at Whitelee's average bid price of £70/MWh, gives a potential value of absorbing this curtailment through EV charging of up to £15.9m[5].

Results

Figures 5.17 and 5.18 show boxplots of the carbon intensity associated with all charge events on all 100 days for uncontrolled charging then controlled charging, with and without consideration of curtailment of Whitelee wind farm (and the setting of grid intensity to zero for these periods). Both the idealised and routine charging cases are shown.

[5]The total cost of the B6 constraint would be the sum of the cost of accepted bids to reduce output and offers to replace it on the other side of the boundary. Therefore, this value is likely to be an underestimate of the true value of absorbing this curtailment as it does not include the cost of accepted offers.

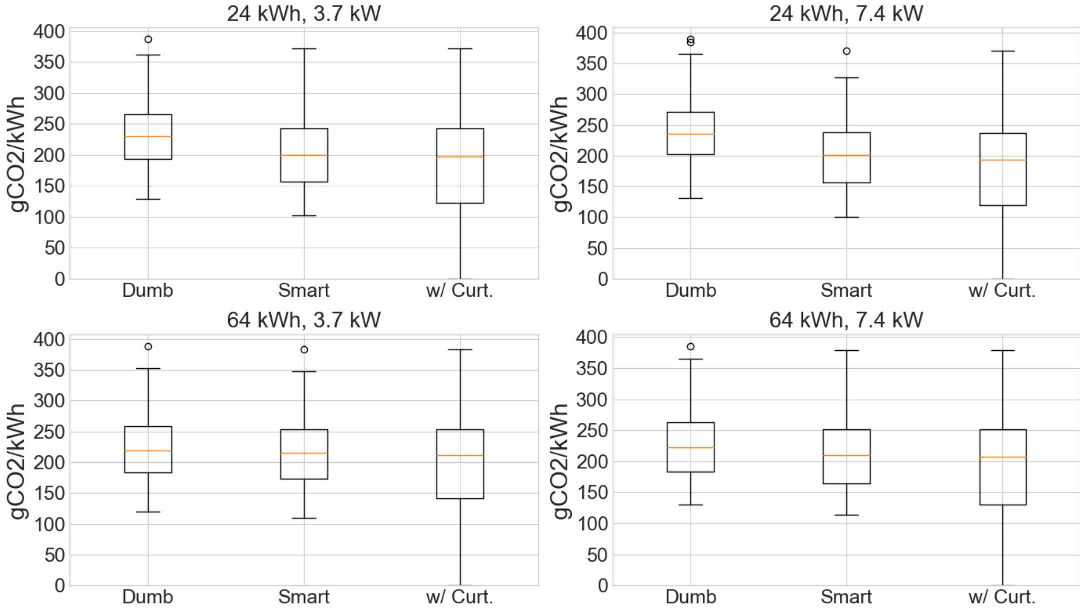

Figure 5.17: Reduction in carbon intensity from controlled charging, with and without the inclusion of curtailment from Whitelee wind farm, for all battery size/charger power combinations – idealised charging behaviour

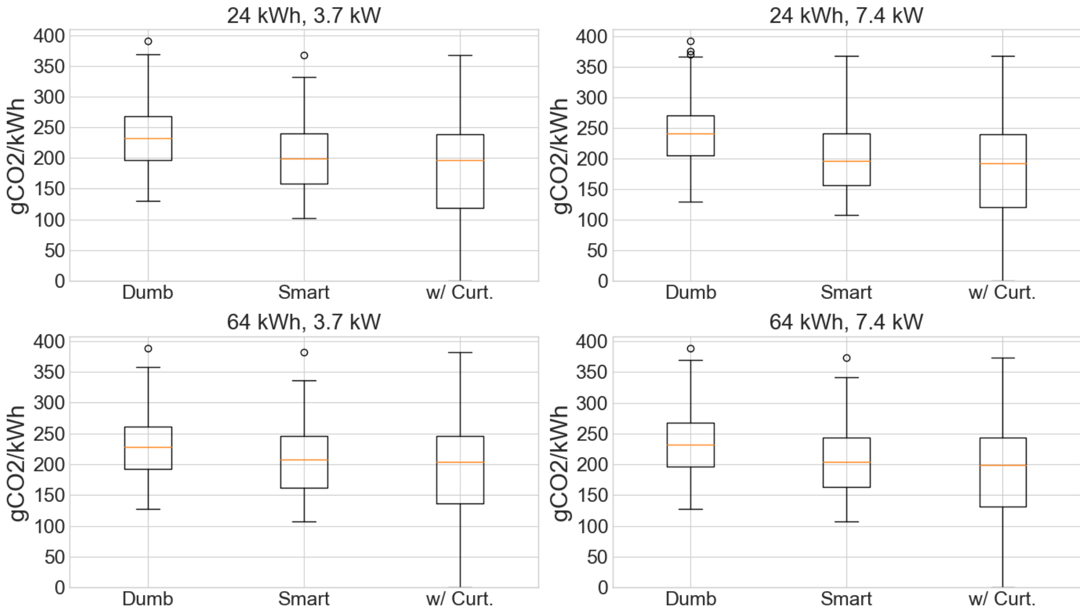

Figure 5.18: Reduction in carbon intensity from controlled charging, with and without the inclusion of curtailment from Whitelee wind farm, for all battery size/charger power combinations – routine charging behaviour

Figures 5.17 and 5.18 show a steady reduction in the carbon emissions associated with EV charging when their demand can be shifted to times of lower carbon intensity. When charging is able to take advantage of excess generation at Whitelee, the emissions associated with charging can be reduced to zero for some cases – corresponding to when curtailment covered a significant proportion of the charging windows. As previously discussed in Section 4.8, the charging load of EVs with larger batteries under the idealised charging model is less flexible than those under the routine charging model. As a result, it is shown that if EV drivers with large batteries only plug in when they need to, it is more difficult for controlled charging to reduce the carbon intensity associated with their vehicles' charging.

The reduction in the mean carbon intensity associated with EV charging for all parameter combinations and both charging scheduling models is shown in Tables 5.4 and 5.5.

Table 5.4: Summary results: reduction in mean carbon intensity of driving (gCO_2/kWh) from smart charging with and without consideration of curtailment of Whitelee wind farm – idealised charging schedules

Mean Carbon Intensity (gCO_2/kWh) – Idealised Charging			
Parameters	**Dumb Charge**	**Smart Charge**	**With Curtailment**
24 kWh, 3.7 kW	234.0	201.7 (-13.8%)	176.2 (-24.7%)
24 kWh, 7.4 kW	241.5	199.7 (-17.3%)	171.4 (-29.0%)
64 kWh, 3.7 kW	221.8	215.0 (-3.1%)	193.5 (-12.8%)
64 kWh, 7.4 kW	226.4	210.5 (-7.0%)	187.1 (-17.4%)

Table 5.5: Summary results: reduction in mean carbon intensity of driving (gCO_2/kWh) from smart charging with and without consideration of curtailment of Whitelee wind farm – routine charging schedules

Mean Carbon Intensity (gCO_2/kWh) – Routine Charging			
Parameters	**Dumb Charge**	**Smart Charge**	**With Curtailment**
24 kWh, 3.7 kW	237.4	200.8 (-15.4%)	172.8 (-27.2%)
24 kWh, 7.4 kW	243.7	201.6 (-17.3%)	172.3 (-29.3%)
64 kWh, 3.7 kW	228.5	208.0 (-9.0%)	182.9 (-20.0%)
64 kWh, 7.4 kW	235.9	205.6 (-12.8%)	179.5 (-23.9%)

If EVs are dumb-charged (i.e. there is no control of their charging), the CO_2 emissions associated with their charging is, on average, in the region 221-243 gCO_2/kWh.

Given that typical electricity consumption values of EVs on the market as listed by the US EPA are in the range from 0.16 kWh/km (based on the city consumption of a 2019 Hyundai Kona Electric 64) to 0.23 kWh/km (based on the highway consumption of a 2012 Tesla Model S 100) [38], this means that the associated EV emissions, if charged from the 2019 GB generation mix without any scheduling of their charging, are in the range 35.4-55.9 gCO_2/km. For context in vehicle emissions, the average tailpipe emissions of new petrol and diesel cars purchased in Europe in 2019 were 121.5 gCO_2/km and 123.4 gCO_2/km respectively [229]. If their charging is not controlled, EVs' carbon intensity is reduced with larger batteries and lower charger power ratings, because this shifts the charging load later into the night (as was found in Section 4.8) when carbon intensity is typically lower (Figure 5.14).

Controlling EV charging, such that all EV charge requirements are met and the network is operated within its thermal limits, without the consideration of any surplus RES generation, can reduce the CO_2 emissions associated with charging by up to 17%. Higher charging power enables the greatest reduction, as this enables more of the energy demand to be met in the times of lowest carbon intensity. Particularly for the idealised charging case, increases in battery size are shown to make it more difficult to reduce the carbon intensity of charging, whereas increases in charger power are shown to make it easier. This is because of the effect of these parameters on the flexibility of charge events, as previously discussed. If drivers plug in routinely, the effect of increasing battery size is diminished.

If there is local RES generation to absorb that would otherwise be curtailed, then in this analysis the carbon intensity was set at 0 gCO_2/kWh for these time periods as per the method used in the National Grid carbon intensity calculator [216]. In this case, controlling EV charging to take place in these periods can further reduce the associated emissions of charging, by up to 29% with respect to the original. Carbon emissions at this level would result in associated emissions of EV driving in the range (using the same energy consumption values as before) 27.6-39.6 gCO_2/km, around a quarter of the corresponding average for petrol and diesel cars.

5.6.2 Controlling Electric Vehicle Charging to Absorb Excess Wind Generation

This section presents an evaluation of the assessment of the extent to which the charging of a large fleet of EVs can be scheduled to absorb surplus renewable generation that would otherwise be wasted, via a case study on Whitelee wind farm.

Method

A single bus model was used (Figure 5.19), with one generator to represent the volume of curtailed wind energy from Whitelee. This can be thought of as, relative to maximum Scottish export capability in each time period, surplus low carbon generation that would otherwise be wasted. The aim is to minimise the surplus that remains unused after charging of EVs. Another generator is used to represent the rest of the GB power system, which has to make up the demand that cannot be satisfied by excess generation at Whitelee.

The volume of curtailed wind is compared for an increasing number of EVs from 10,000 to 1,000,000, for both the idealised and routine charging cases. For context, there are currently over 2.4 million private cars in Scotland [230] and, based on the Scottish Government's target for all sales of new cars and vans to be zero emission by 2032 [231], it is reasonable to expect that there could be at least a million battery EVs within the Scottish 'Central Belt', where approximately 65% of the population live (i.e. behind the B6 boundary constraints which result in curtailment at Whitelee).

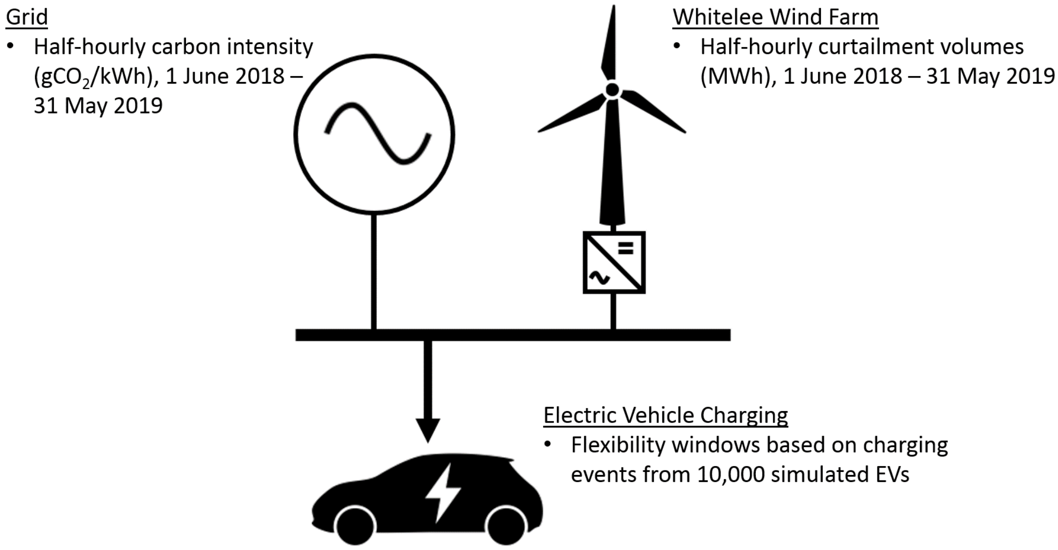

Figure 5.19: Schematic showing single bus model used to study potential of EV charging to utilise excess wind generation

Simulating up to 1,000,000 individual EVs was not possible as this would exceed the amount of travel data on record. 10,000 simulated EVs were scaled up to 50,000, 100,000, 250,000, 500,000, 750,000 and 1,000,000 EVs by multiplying the battery capacity C_e, charger power P_e^{DC}, initial energy storage content E_e^s and final energy storage content E_e^d of each EV accordingly. This approach of aggregating EVs to form large flexible demands has been demonstrated before – as previously discussed in Section 5.2 – in [207] and [208].

Note that LV network constraints are not considered in this part of the work due to the computational burden involved, and it is recognised that this could limit the flexibility available from EVs. Managing distribution network constraints, and coordinating access to flexible assets between distribution and transmission level markets is a subject of ongoing research [232–234], though is outside the scope of this study.

The battery capacities, charger power and level of access to charging of the EVs are assigned to vehicles using the same distributions as used in Section 5.4.

The DCOPF formulation presented in Section 5.3 was used to minimise carbon intensity as in the carbon intensity minimisation study. The output of the wind generator in Figure 5.19 was limited to the total curtailment in each period (5.14).

$$p^G_{w,\tau} \leq P^{UB}_{w,\tau} \tag{5.14}$$

where $p^G_{w,\tau}$ is the active power contribution from the wind generator in the time period $[\tau, \tau + 1]$ and $P^{UB}_{w,\tau}$ represents the maximum power output from the wind generator in the time period $[\tau, \tau + 1]$, equal to the average curtailed wind power in that same timestep at Whitelee. Therefore, in periods with no wind curtailment, $P^{UB}_{w,t}$ is zero.

The wind generator was modelled as having 0 g/kWh carbon intensity and the grid (which makes up the remainder of charging demand that the output of the wind farm cannot) was modelled as having the national carbon intensity [216] (matched to the same 112 days for which there was curtailment at Whitelee).

Results

Figure 5.20 shows boxplots of the percentage reduction in curtailment on each of the 112 days with curtailment in the period 1 June 2018 to 31 May 2019 for fleets of EVs of various sizes. Figure 5.21 shows the total percentage reduction in curtailment over the whole period for the same fleet sizes.

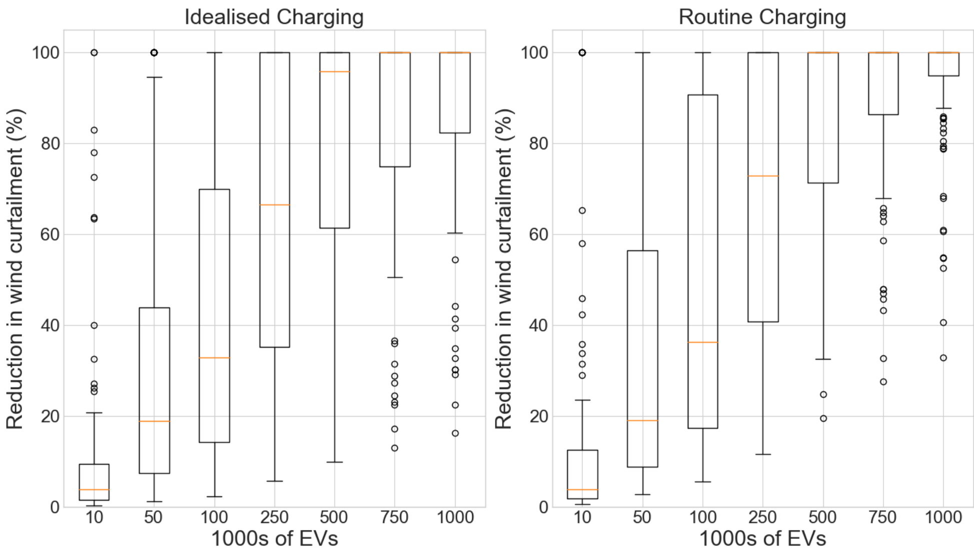

Figure 5.20: Box plots showing percentage reduction in wind curtailment at Whitelee wind farm on 112 days with curtailment from the optimisation of charging from fleets of EVs of various sizes (1000s)

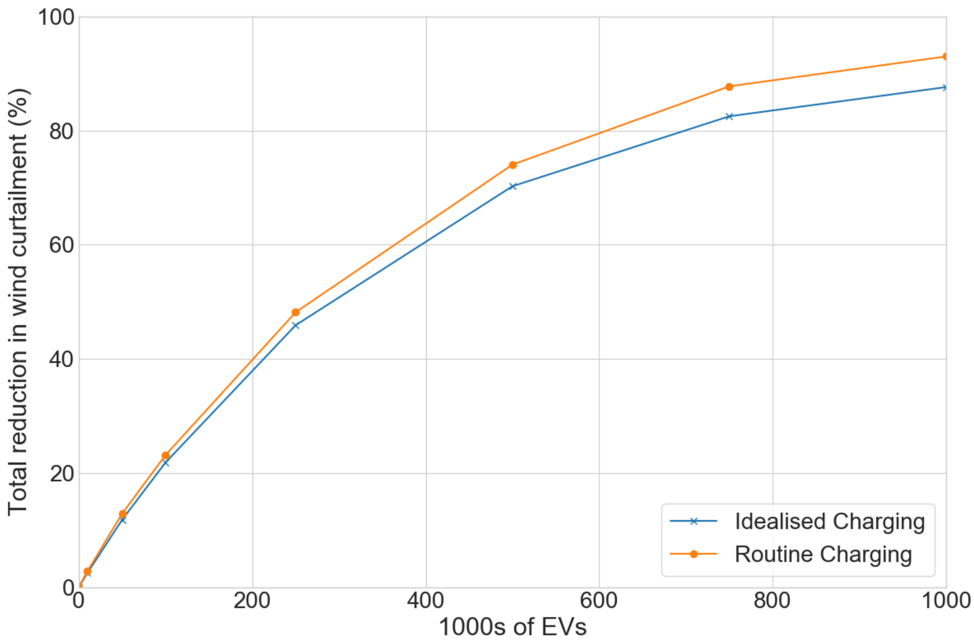

Figure 5.21: Total reduction in curtailment of generation at Whitelee wind farm over period 1 June 2018 to 31 May 2019 from the optimisation of charging from fleets of EVs of various sizes (1000s)

Figure 5.20 shows the rate of increase in curtailment reduction as the fleet of EVs increases in size. While the variance is high (due to the variance in the volume of curtailment on each day and the time of day at which this occurs), it is shown that the reduction in curtailment continues to increase with an increasing size of EV fleet. Figure 5.21 shows that this rate of increase is diminishing; this is due to a subset of days for which the curtailment cannot be reduced to zero even by the charging of 1,000,000 EVs. These are days in which a large volume of curtailment occurs in the middle of the day (when there are fewer EVs plugged in); however, as shown in Figure 5.16, wind curtailment in the daytime is rarer than in the nighttime.

It is shown in Figure 5.21 that if drivers plug in and charge routinely, then there is more potential for EV charging to be able to reduce curtailment. This effect is most pronounced for large fleets: with a fleet of 1,000,000 EVs, whereas 93.0% of Whitelee wind farm's total curtailment can be used to charge these EVs if they are plugged in routinely, 87.6% of total curtailment can be used for the idealised charging case. The reason for these numbers not being vastly different is that the energy for these EVs to carry out their transport requirements remains the same for both cases – though the extra flexibility resulting from routine charging can be better utilised to reduce curtailment at the wind farm. Given that the absorption of this curtailment potentially has significant value, it could be expected that drivers could be incentivised to plug in routinely when arriving home so as to maximise any revenue that may be made from the absorption of curtailment.

5.7 Chapter 5 Conclusions and Further Work

5.7.1 EV Charging for Management of Network Constraints

The Future of Controlled EV Charging

It was shown in Section 5.4 that although a 'valley filling' optimisation approach could reduce the impact seen by the network, it was not possible to accommodate the charging of 100% penetration of EVs in the Pollokshields network within GB statutory voltage limits. Furthermore, although this approach could reduce the network impact, there remains a rift between what is mathematically possible and what is attainable in the real world. A controller of EV charging (e.g. an aggregator) would not have a projected schedule of vehicle arrivals and departures and each of their energy storage contents before they arrive.

Some of the simple heuristic methods were shown in Section 5.5 were shown to be relatively effective at controlling charging within network limits (at least, comparable to the formal optimisation) and providing the majority of vehicles with enough energy to be able to make it to their next charging opportunity, though this was dependent on charging behaviour – if drivers plug in routinely, their individual energy requirements tends to be smaller and hence they were more likely to be met. However, it is stressed that a limitation to the analysis performed is that it only considered one 24 hour period, and as such does not consider the knock-on effect of missing out on charging energy on travel plans over a longer period. A piece of further work is recommended to quantify what this might be, to further illustrate the viability of using such heuristic methods to schedule EV charging. The simple delay method is not suitable for the management of EV charging; although techniques similar to this have been deployed in practice (e.g. [211,213]), it was found in this analysis that this method can increase the network peak and introduce a severe ramp rate which may bring problems to system frequency stability.

The downside to the use of the heuristic methods is that they will not necessarily ensure that the network is operated within its limits, nor that the fleet of vehicles charging is provided with the same amount of energy that they would have received from uncontrolled charging. The methods presented in Section 5.5 could potentially be made resilient to achieving both these goals by the optimisation of their operation (for example, in terms of the spacing between vehicles starting charging in the queue delay algorithms, or the setting of the peak time during which no charging is allowed to happen) for various scenarios pertaining to EV parameters, network characteristics and social demographics.

Though the perfect foresight of charging schedules as used in Section 5.4 is an unrealistic ideal on which to be able to manage charging, the diversity in the charging requirements placed on a network of as many customers as the Pollokshields network

– given that all results presented in this chapter have been based on MC-style simulations in which different vehicles with different travel diaries are applied to the network each time – has been shown throughout this thesis to be low. Therefore, these likely requirements could be learnt by a controller and these could be updated as inputs which have been shown to strongly influence the resulting charging demand (EV parameters, charging behaviour and demographics) may change in time. A valuable piece of further work from the analysis presented in this chapter would be to develop a machine learning approach to charging optimisation that could learn likely charging requirements based on a set of input parameters, based on the information that it could have access to (arrival times of vehicles that have arrived so far, their battery size and SoC), and manage the charging load in such a way that it would be *likely* to provide vehicles with the amount of energy they require in a way that maintains the operation of the network within limits.

Distribution System Voltage Limits

Due to memory constraints on the computing resources available during this study, the valley-filling optimisation approach presented in Section 5.4 was formulated as a DCOPF problem, i.e. it neglected variation in endpoint voltage. Although the results of these minimum loading charging schedules were then input into an AC load flow to return the effect on endpoint voltage, the optimisation could be improved by making it into an ACOPF formulation. This could be achieved by decomposing the network into smaller portions and solving individually, before aggregating the solutions to provide one overall solution. However, this approach is far from trivial: the assumptions regarding the voltages at each secondary transformer, as a result of loading in other parts of the network, would not be a simple assumption to make. Further work is recommended in exploring how these formulations might be made effectively.

Even as a result of the 'best case' valley-filling of EV charging load presented in Section 5.4, the network could not be kept with statutory GB voltage limits. This is an important result in itself, as it suggests that no matter how their charging is managed, the Pollokshields network (and likely many other residentially-dominated networks in

GB) cannot support a 100% penetration of EVs if it is assumed that the primary substation LV bus is at 1 pu.

There could be several solutions to these voltage deviations. By employing remote monitoring around the network, the primary substation could adjust its tap settings in real time to manage the voltage within the acceptable limits. Another possibility is the use of reactive compensation. However, an easier and lower-cost solution may be to simply relax the voltage constraints themselves. In Western Power Distribution's 'Enhanced Voltage Assessment' method within their *Equilibrium* innovation project, they estimate that on the basis of six separate substations, an increase of at least 24% of demand capacity could be realised by relaxing the minimum distribution level voltage limit from -6% to -10%, with no noticeable effect on electrical device performance [235]. Furthermore, if a majority of load served in a network is of the constant impedance type, a reduction in voltage could reduce network losses [236] and therefore overall energy consumption [237]. As shown in Table 5.1, the optimised charging schedule – even under routine charging behaviour – was able to keep voltage drop within 10%.

Bidirectional Charging (V2G)

Bidirectional EV charging (a.k.a. V2G) is increasingly part of the discussion regarding the management of EV charging in a distribution network context. For example, using UK travel statistics and loading data as a case study, the authors in [238] find that there is a potential 35% reduction in network peak following the application of V2G. In the commercial space, the concept is becoming widely known. For example, the Octopus *Powerloop* V2G tariff offers up to £30/month off the lease of a new EV in return of the supplier being able to sell services back to the grid on behalf of the EV owner, while the OVO V2G trial offers annual savings of £570 [239]. Based on this, it seems that V2G could have the potential to help manage the integration of EVs in LV distribution networks. A valuable piece of further work would be to include bidirectional charging in this analysis, to quantify the potential to which any impact on the network could be further reduced.

5.7.2 EV Charging to Support Renewables

Carbon Emissions of EV Driving

It was found through analysis presented in Section 5.6.1 that if EV charging were able to follow the times of low carbon intensity and take advantage of RES curtailment, then the emissions associated with their charging was shown to be in the region 27-40 gCO_2/km; a 30% reduction on the 'dumb charging' carbon intensity of 35-56 gCO_2/km. This offers an improvement of up to a factor of 5 relative to average new petrol and diesel cars.

It is important to note that in this work the carbon intensity of the grid has been modelled as independent of demand and therefore it has been assumed that the marginal increase of EV charging will not lead to an increase in carbon intensity of the grid (through dispatch of fossil fuelled generation). Although the scale of modelling means that the load presented by the EVs' charging is negligible in comparison to GB demand, if such a scheme were implemented on a large (e.g. nationwide) fleet of EVs then their charging would effect grid intensity – if their charging were to come online such that dispatchable thermal plants had to be brought online, then the carbon intensity associated with their charging would be equivalent to the carbon intensity of the dispatchable plant. Furthermore, the sudden increase in demand could present problems to the stability of system frequency. However, there are several electricity tariffs on offer in the UK at present aimed at EV drivers with access to private residential charging, which offer varying electricity prices based on forecasts of RES output and wholesale electricity prices [240–242] – in which the agreed prices, generally settled with customers some hours before the charging period, do not change if other EVs also suddenly begin charging at that time. As the penetration of RES continues to increase in line with government targets, an increased variance in grid intensity is likely. By following the times of lowest grid intensity, the presence of EVs would effectively be incentivising further RES generators to come online by providing a greater level of certainty that the energy they generate would be consumed, even if produced outside of a traditional domestic demand peak.

Flexible EV Charging to Absorb Excess Renewable Generation

It was shown in Section 5.6.2 that there is significant potential to absorb excess RES generation from the flexibility of EV charging: a fleet of 500,000 EVs, which would equate to an EV penetration of approximately 20% based on Scotland's total car fleet of 2.4 million, could absorb approximately three quarters of curtailment at GB's largest onshore wind farm as experienced in the time period 1 June 2018 to 31 May 2019. As Whitelee represents only part of the curtailment (11.5%), there is significant potential for smart charging of EVs to reduce this curtailment as a credible alternative to grid reinforcement[6].

A potential market mechanism to reward EV flexibility for reducing wind curtailment is the GB balancing mechanism (BM). Aggregated EV flexibility could be accessed by National Grid ESO in the BM to manage transmission system constraints, offering an alternative to wind curtailment (i.e. rather than paying wind generators to turn down their output, the ESO could pay EV charging aggregators to turn up their demand). However, access to the BM is currently limited for smaller participants such as EVs – this is due to the economics of scale favouring a smaller number of larger units, the requirement for any participant to be a fully licensed supplier (unless granted a derogation by the regulator) and the ESO favouring larger units in the BM at short timescales [243].

However, the introduction of the 'virtual lead party' under the GB implementation of project TERRE will allow smaller aggregators (with a minimum aggregated BM unit size of 1 MW) to participate in the BM without the need to be fully licensed suppliers [243, 244]. Furthermore, the ESO has introduced a distributed resource desk, which has resulted in increased participation of industrial and commercial aggregators in the BM [245]. Coupled with the projected growth in EV penetration, this reduction in the barriers to access the BM is likely to contribute positively to the business case of aggregation of EV charging for the provision of grid services.

[6] Such as the Western Link, a 2.2 GW HVDC subsea cable commissioned in 2017 between Hunterston in West Scotland and Flintshire Bridge in North Wales to reduce the amount of Scottish wind curtailment by providing extra transmission capacity from Scotland to the rest of GB. Note that the amount of curtailment reported at Whitelee as used in this chapter is inclusive of that which has been reduced by the Western Link.

Chapter 6

Conclusions and Further Work

The electrification of the private vehicle fleet, coupled with a low carbon generation mix, is likely to be a key contributor to going *net zero*. However, electric vehicles are fundamentally quite different to the conventional vehicles that most people drive at the moment: their capacity for energy storage is far smaller, and the rate at which it can be replenished is much slower. For EV uptake to increase to the levels required, EVs must be perceived as of negligible inconvenience relative to petrol cars, or at least that any inconvenience they do carry is balanced out by other favourable effects, lower running costs and the feeling of 'being green' being two of these. Furthermore, whereas ICVs take their energy from a system that has been designed around them, from crude oil extraction to refineries to petrol stations, EVs take their energy directly from our electricity system which, crucially, has not been designed with them in mind. Moving all the energy currently used by the transport sector – equivalent to 57 million tonnes of oil per year [246] – onto our electricity system will obviously not be without impact. The greatest impact is thought to be at the ends of the distribution network, where relatively low-capacity lines, not designed to be able to meet the energy demands of cars, feed domestic properties.

The goals of this thesis were (i) to quantify the likely impact of the electrification of private transport on potential consumers and the power system, and (ii) to evaluate the potential of the management of their charging to avoid costly network reinforcement and even benefit the power system by selectively charging in times of excess renewable generation.

Chapter 2 provided quantification of the convenience of EV charging relative to ICV fuelling (as equating convenience to the total time penalty experienced); Chapter 3 provided characterisations of the likely variation in demand from en route and public destination charging using a ubiquitous source of smartphone locational data; Chapter 4 provided analysis into the likely impact of uncontrolled EV charging on distribution networks, including insight into the effect of charging behaviour, demographics and the shifting technological and charging access patterns as a result of the evolving EV market; Chapter 5 provided quantification of the potential for controlled charging to (i) mitigate the issues found to be likely from the analysis in Chapter 4 and (ii) enable further decarbonisation of the electricity system by charging selectively when grid carbon intensity is low and wind curtailment is high.

6.1 Summary of Contributions

In Chapter 2, it was shown that the transition from ICVs to EVs will affect people differently, depending not only on their patterns of usage of their vehicles but the technical specification of their vehicles (battery capacity and charger power rating) and the number of locations they can charge at. It was found that although the majority – up to 95% – of individuals who can charge at home are expected to be able to reach convenience parity (such that there is no inconvenience resulting from switching from an ICV to an EV) with battery sizes currently available in EV models at the 'affordable' end of the market, this is significantly less likely for those who rely on workplace or public charging – and particularly for those who must rely solely on en route charging. These individuals are expected to suffer considerable inconvenience associated with EV charging relative to ICV fuelling, and although greater battery capacities and charger power ratings are expected to lessen this inconvenience, there remains a significant gap in the convenience of EV ownership between those who can charge while parked at home and those who cannot. Therefore, it is recommended that alternative methods of providing at-home parking (e.g. on-street home charging via lampposts or kerbside sockets) are supported in lessening this gap.

Furthermore, analysis was carried out with respect to long journeys that cannot be made on a single charge, 'range anxiety' being a major obstacle to widespread EV adoption. It was found that if drivers are compliant with the UK Highway Code in taking regular breaks on long journeys, fewer than 0.01% of trips are expected to be delayed by charging when using battery capacities of 40-60 kWh.

The main conclusion offered by Chapter 2 is that we risk a substantial increase in 'mobility inequality' between those who can charge at home and those who cannot. It begs the question; if every new car in the UK is expected to be electric by 2040 (or 2032 in Scotland), what are individuals who lack access to charging expected to do? This inequality is reduced significantly if charging power is increased and drivers are provided with at least some access to parked charging, which may be located at workplace car parks or public destinations.

This conclusion made in Chapter 2 gave rise to the analysis presented in Chapter 3, which sought to model the likely demand from EV charging at these public destinations and en route charging stations using data from a widely-used Smartphone app: Google Maps. It was demonstrated how such a dataset can be used to simulate the arrival rate of EVs to hypothetical charging infrastructure at a destination, assuming that the arrival rate of drivers looking to charge their EVs is proportional to the arrival rate of visitors to that destination. It was found that the temporal variation in charging demand from public destination charging stations is likely to vary significantly based on what kind of destination it is and the day of the week. It was shown that the method can be applied to hypothetical charging infrastructure at a particular amenity (e.g. Braehead shopping centre) to derive the likely demand profile from EV charging there. This approach could be valuable to system planners in the current absence of data on how EV charging infrastructure is used (given that EV penetration is currently low, usage patterns are likely to be very different now than in the future).

While public and en route charging is likely to be an important part of the mix, it was shown in Chapter 2 that having access to charging at home is the most effective way of enabling EV users to achieve convenience parity with ICV users. Therefore, it is reasonable to expect – as is stated by the UK Government [135] – that if drivers can charge at home, they will do so. To this end, Chapter 4 presented analysis of the likely impact of uncontrolled EV charging at home on residentially-dominated distribution networks. Network models were developed from two real distribution networks in Glasgow's Southside region: Pollokshields, which represents an affluent suburban area where car ownership is higher than the Scottish average and Gorbals, which represents a historically deprived inner city area where car ownership is lower than the Scottish average.

As explained in Section 4.2, there are advantages to using both EV trial data and travel data as a basis from which to model charging demand. Therefore, both were presented: firstly, charge event data from the *My Electric Avenue* EV trial was used to analyse the impact of EV charging on the Pollokshields network if vehicles within the network are assumed to be as likely to be charging as vehicles in the *My Electric Avenue* (MEA) trial. Following this approach, it was found that when 40-70% of vehicles in the network are replaced by EVs, the operation of the network is likely to stray outside of its limits. The main limitation of this assessment approach is that it effectively fixes the results to one set of EV parameters (battery size, charger power and set of locations at which they can charge) and one comparatively small set of individuals, who are likely to adopt a subset of behaviours based on their willingness – and eligibility – to participate in the trial. Therefore, an approach using the NTS travel diaries as used in Chapter 2 was also presented. This was used to consider the effect of any variation in driver behaviour (by presenting two methods of deriving likely charge events from the week-long NTS travel diaries), key demographic indicators (employment type and means of travel to work) and changing EV parameters (battery capacity, charger power and level of access to charging) on the resulting charging demand. The resulting charging demand when derived from the NTS data was found to be higher than that when using the MEA data, for the same 'base case' of parameters to match the vehicles used in the trial – this was the case no matter which method was used to derive the charge schedules. Out of the two methods of deriving charge events from travel data, the likely spread in resulting charging demand profiles was returned. Whereas the idealised method (in which drivers seek to minimise the number of plug-ins) returned the lowest total charging demand due to the increased diversity in charging behaviour, the routine method (in which drivers will always plug in on arrival at home) returned the highest peak charging demand, and lead to the most drastic violations of network limits.

The investigation of the effect of social demographics was done by carrying out the analysis on the Pollokshields and Gorbals networks. It was found that the impact of EV charging would be significantly greater in Pollokshields than it would be in Gorbals and that the increase would be disproportionate compared to the increase in the number of vehicles, due to the differences in travel habits reported between individuals within the different demographic groups. This raises some further questions about how any network reinforcements would be paid for, given that this analysis would suggest certain areas (those typified by high car ownership and employment rates) will require reinforcement before others.

Chapter 4 also presented an investigation of the effect of EV parameters on their resulting charging demand and the impact on distribution networks. It was found that out of the key emerging patterns identified in the evolving EV market, larger batteries and more widespread charging access may reduce the peak demand from EV charging and/or shift it to a time less likely to coincide with peak domestic demand. On the other hand, increasing charging power may increase the peak and bring it closer to a time where it is more likely to coincide with peak domestic demand.

The work in Chapter 4 explored several factors in determining the impact of EVs charging on distribution networks. A common theme that emerged from all of them is that a high penetration of EVs is likely to present problems to the distribution network and it is clear that there are sets of circumstances which would lead to severe consequences in terms of overloading and undervoltages. The work presented in Chapter 5 – an investigation into the opportunities of managed charging – arose out of this conclusion.

Using the basis of the modelling carried out on the Pollokshields network presented in Chapter 4, a valley-filling DCOPF approach was presented in Chapter 5 to attempt to manage charging within network limits. It was found that even when charging is scheduled for the minimum possible total demand, the network in the case study could not be kept within statutory GB voltage limits. This is an important result in itself, as it suggests that no matter how their charging is managed, the Pollokshields network (and likely many other residentially-dominated networks in GB in relatively better-off areas) cannot support a 100% penetration of EVs if it is assumed that the primary substation LV bus is at a voltage of 1.0 pu. While other methods of regulating system voltages were discussed, evidence was provided that suggests that these voltage limits could be relaxed without any detrimental effect to the appliances connected.

In reality, any agent acting to manage EV charging within a network (e.g. an aggregator or DSO) would not have perfect foresight of the future arrivals of vehicles. Therefore, a set of low-information heuristic-based methods, which could operate in real time from the level of information ascertainable from a smart meter, were presented in comparison to the valley-filling optimisation. It was found that some of the heuristics presented, notably the lowest range first served (LRFS) approach, in which vehicles are queued to begin charging in the order of increasing remaining driving range, could maintain the system within similar voltages as the valley-filling optimisation approach at the expense of fewer than 0.02% of vehicles plugged in having to stop to charge before their next charging opportunity as a result of less energy being transferred due to the charging management system. However, this was analysed on the basis of one 24-hour charging period. There may be knock-on effects from the restriction of charging every night, and further analysis is recommended to examine this.

Work presented in Chapter 5 showed that there is significant potential for EV charging to interact positively with the power system. If EV charging were able to follow the times of low carbon intensity on the present day GB power system and take advantage of RES curtailment, then the emissions associated with their charging was shown to be in the region 27-40 gCO_2/km, a 30% reduction on the 'dumb charging' carbon intensity of 35-56 gCO_2/km. This offers an improvement of up to a factor of 5 relative to average new petrol and diesel cars sold in Europe (121.5 gCO_2/km- 123.4 gCO_2/km for petrol and diesel respectively [229]). It was also shown that there is significant potential to absorb excess RES generation from the flexibility of EV charging: a fleet of 500,000 EVs, which would equate to an EV penetration of approximately 20% based on Scotland's total car fleet of 2.4 million, could absorb approximately three quarters of curtailment at GB's largest onshore wind farm.

6.2 Further Work

As demonstrated in Section 6.1, this thesis has made several contributions to the body of research surrounding the likely impact (both positive and negative) of the electrification of private transport on our power system. However, there are of course many possible developments that could prove valuable future work in further broadening our collective understanding of the subject. This section outlines some thoughts on possible future work.

Further Disaggregation of Travel Habits

The work presented in Chapter 4 presented some disaggregation of travel habits on the basis of two demographic indicators (employment type and means of travel to work) that were found to affect individuals' travel habits. The integration of this into an electrical network model represents the first attempt in the academic literature – to the author's knowledge – at analysing the likely impact of EVs on the power system taking into account the variability of travel habits based on demographic indicators within an electricity network. However, this disaggregation could be made more detailed: as already mentioned, travel habits are influenced by income, employment status and geographical location [159–161]. Though this level of detail is not available in the NTS dataset, further research could be conducted to bring together datasets which do involve a greater level of detail. For example, while it does not contain detailed trip data, data from annual car road worthiness tests (so-called MOTs) can be used to examine the spatial variation in total transport energy demand, given by the vehicles' annual mileage (as the results are connected to geospatial locations) [247]. Datasets such as these could be used to further understand the likely differences in EV impact on urban networks, such as those analysed in this thesis, and those of commuter towns and rural locations where mileage tends to be higher [248].

The Future of Managed EV Charging

In reality, the control of EV charging must be done in a way that relies on the level of information that is available to the party that is controlling the charging. Though a valley-filling optimisation based on having a perfect foresight of vehicle arrivals is unrealistic, the diversity in the charging requirements placed on a network was found to be low. Therefore, these likely requirements could be learnt by a controller and these could be updated as inputs which have been shown to strongly influence the resulting charging demand (EV parameters, charging behaviour and demographics) may change in time. This could also include bidirectional charging, in which EVs could discharge power to the grid if necessitated by the charging demands of other vehicles, or some other demand in the network. An interesting and valuable piece of further work could be the design and testing of a machine learning approach to the scheduling of EV charging given the travel diary/charging schedule analysis presented in this thesis.

Bidirectional Charging (V2G)

V2G is now part of the mainstay of discussion regarding the future of EVs. As aforementioned in Section 5.7.1, work recently published in [238] found that the peak loading on a representative GB distribution feeder could be reduced by 35%. Furthermore, the ability to inject power into the grid could increase the functionality in EVs' participation in the balancing market [50]. Though the work published in this thesis regarding the synthesis of charging schedules based on real travel data and the application of these charging schedules to the network using a sociotechnical model that takes into account the demographics of the local area represents a significant contribution, it would be a valuable piece of further work to expand on this by including the potential for vehicles to discharge to the grid.

EVs as Part of the Future Transport System

It has been assumed throughout this thesis that individuals in the future will continue to drive the way they do now, that commuting and activity patterns will go unchanged. While this may be reasonable, given that travel habits have remained virtually static for nearly the last two decades (see Figure 4.23), shifts in technology such as the advent of autonomous vehicles and car-sharing may mean that vehicle usage patterns look quite different in 2040 to how they do now. Furthermore, growth in flexible working patterns and better communications technology coupled with renewed emphasis on public and active transport (i.e. walking and cycling) may mean that our car-based energy demand could fall over the next few decades. A valuable piece of future work would be to analyse likely transport system scenarios as proposed in policy, and translate that to car-based demand and hence EV charging demand. From there, the impact on the energy system on the resulting cost could be evaluated for a wide range of scenarios pertaining to the decarbonisation of the transport sector.

Epilogue

The electrification of transport is not an end unto itself but a means to an end of a *net zero* energy system. ‘Clean growth’ as part of a *just transition* [249] means more than attending to carbon implications but growing an **inclusive** *net zero* economy. As identified in this thesis, there are potential obstacles to the electrification of private transport making this happen all by itself.

It has been shown that the widespread uptake of EVs and their charge points will require significant upgrades to our distribution networks. The costs of these upgrades are currently shared amongst all energy consumers by ‘use of system charges’ included in our bills [250]. These charges – for those connected at LV – are based on our annual energy demand (rather than our peak power), but because networks are built based on the peak flow, these charges only have a limited correlation with our impact on the need for reinforcements. It was shown in Chapter 4 of this thesis that, if uncontrolled, EV charging is likely to disproportionately add to the network peak. Furthermore, any remuneration that EV owners may receive from the provision of grid services will be funded by energy billpayers[1].

This means that while we will likely all fund the transition to EVs through increased energy bills, only a select few will reap the direct financial benefits: at the end of 2018, only 78% of households in the UK owned a car or van [252]. Based on a Department

[1]Of course, the provision of ancillary services from EVs could be a lower cost (and more environmentally sound) means of grid frequency support than, for example, part-loaded open cycle gas turbines. However, a comparable scheme may be feed-in tariffs offered to households with rooftop PV: it was shown by Government analysis [251] that whereas the costs of the scheme are born by the poorer sections of the population as much as the better-off, the benefits are disproportionately realised by the better-off – therefore, the scheme played some part in exacerbating fuel poverty. Regulation of the involvement of EVs in the power system is required to ensure that they can contribute effectively to the *just transition*.

for Transport survey [26], only 57% of UK households have access to off-street parking and therefore would have somewhere to install a home charge point.

Unequivocally, removing the tailpipe emissions from road vehicles will help. However, a future transport system based on the private car is inherently inefficient and has further negative consequences. The Department for Transport's own traffic forecast [253] states that the uptake of EVs is likely to put more pressure on traffic growth by lowering the costs of motorised transport. The widepsread provision of public charging was discussed in Chapter 2 of this thesis to be a potential leveller in EV charging convenience between those who can charge at home and those who cannot. However, by incentivising drivers to make these journeys by car rather than another means due to the opportunity to charge their vehicles, we could see an increase in car dependency. Continued car dependency leads to more inactive lifestyles, congestion and the transformation of our urban spaces to giant car parks. Local authorities and urban planners from Lyon [254] to Birmingham [255] and Glasgow [256] are planning for a future with drastically reduced car dependency in urban areas, at the promotion of active travel (i.e. cycling and walking) and public transport. Transport Scotland's 2019 *National Transport Strategy* emphasises the focus of a 'Sustainable Travel Hierarchy', in which the private car appears at the bottom of a hierarchy of transport modes to promote the use of.

Some journeys necessitate the use of cars, and it is these journeys that must be replaced by vehicles that do not emit greenhouse gases. However, the transition to the future transport system presents opportunities, not only to eliminate emissions from the tailpipes of our vehicles or to support further deployment of intermittent renewable generators by providing flexible EV charging demand, but to make our forever changing habitat a better place to live.

Appendix A

Derivation of Beta Parameters for Battery State of Charge on Arrival from EV Trial Data

Journey and charge event data are taken from two real EV trials: *My Electric Avenue* (MEA) as used in Section 4.5 and *SwitchEV* [130]. *SwitchEV* was a 26-month long project (March 2011 to May 2013) that ran in the Northeast of England as part of the Technology & Strategy Board *Ultra Low Carbon Vehicle* demonstrator programme. In the project, 44 EVs from five suppliers (all with a battery capacity of 16 kWh) were leased to members of the general public. All driving and charging events in the project were recorded, resulting in records of 62,060 trips and 16,229 charging events. Due to its significantly larger number of charging events (as stated in Section 4.5.2, the MEA trial consisted of 371,293 trips and 76,698 charging events) and its focus on residential charging, MEA data was used to characterise charging at home. Data from *SwitchEV* was used to characterise charging at workplace and public destinations, as unlike the MEA dataset, the location of charging (home/work/public) is labelled in the *SwitchEV* dataset.

EV Trial Data for the Derivation of Probabilistic Charging Schedules

Figure A.1 shows key data for weekdays from both EV trials. Aside from the SoC that the vehicle finds itself in at the end of the trip, the time of day is also likely to influence a driver's decision whether to charge or not. Evident from the plots on the middle row of Figure A.1, different types of charging are expected to happen at different times of day. As discussed in Section 4.5, there is a clear peak in the home charging data in the period 15:00-21:00 likely due to drivers arriving home from work. For the workplace charging data, there is a peak in the period 06:00-10:00, likely due to drivers arriving at work. The morning and evening peaks in the public charging data are less strongly defined. All three of these patterns are in alignment with the travel behaviour exhibited in the NTS data (Figures 4.29-4.31).

The bottom row of Figure A.1 shows CDFs for the SoC at the start of the charging event defined for three time periods, so as to extract an influence of the time of day on driver's likelihood of charging. These are set as morning (06:00-10:00), evening (15:00-21:00) and off-peak, which includes both the middle of the day (10:00-15:00) and the night-time (21:00-06:00).

Figure A.2 shows the same results for the weekend data. Due to there being less charge data from the weekend days, it is harder to imply any statistical significance in the shape of the charging frequency profiles (middle row). Therefore, CDFs are shown for the whole weekend days as one, rather than being split into three periods as in the weekdays analysis. As in common with Section 4.5, the impact of weekend charging is not analysed in this section and the distributions in Figure A.2 are for comparison only.

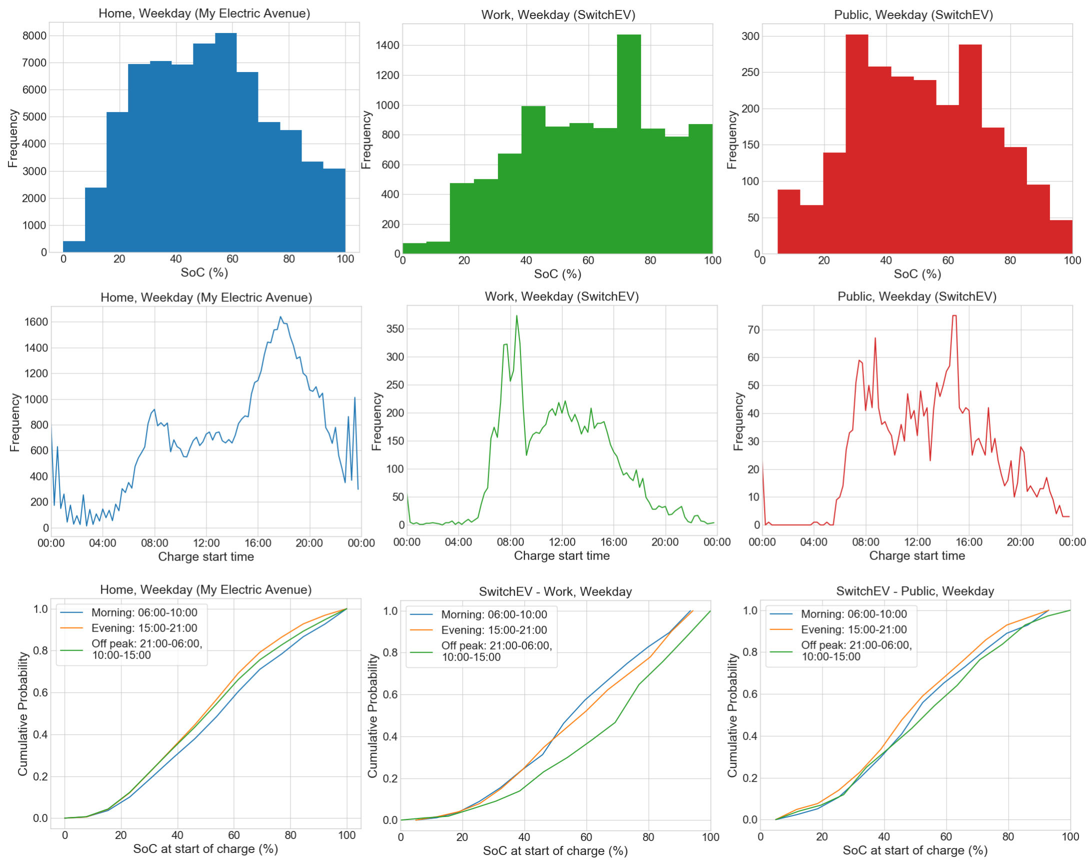

Figure A.1: Key EV trial data for weekdays (*My Electric Avenue*; *SwitchEV*) for deriving distributions of charging probability given battery state of charge. Top row: histograms showing state of charge at plugin, middle row: plots of charge plugin time, bottom row: cumulative distribution functions for state of charge at plugin for 3 distinct time periods

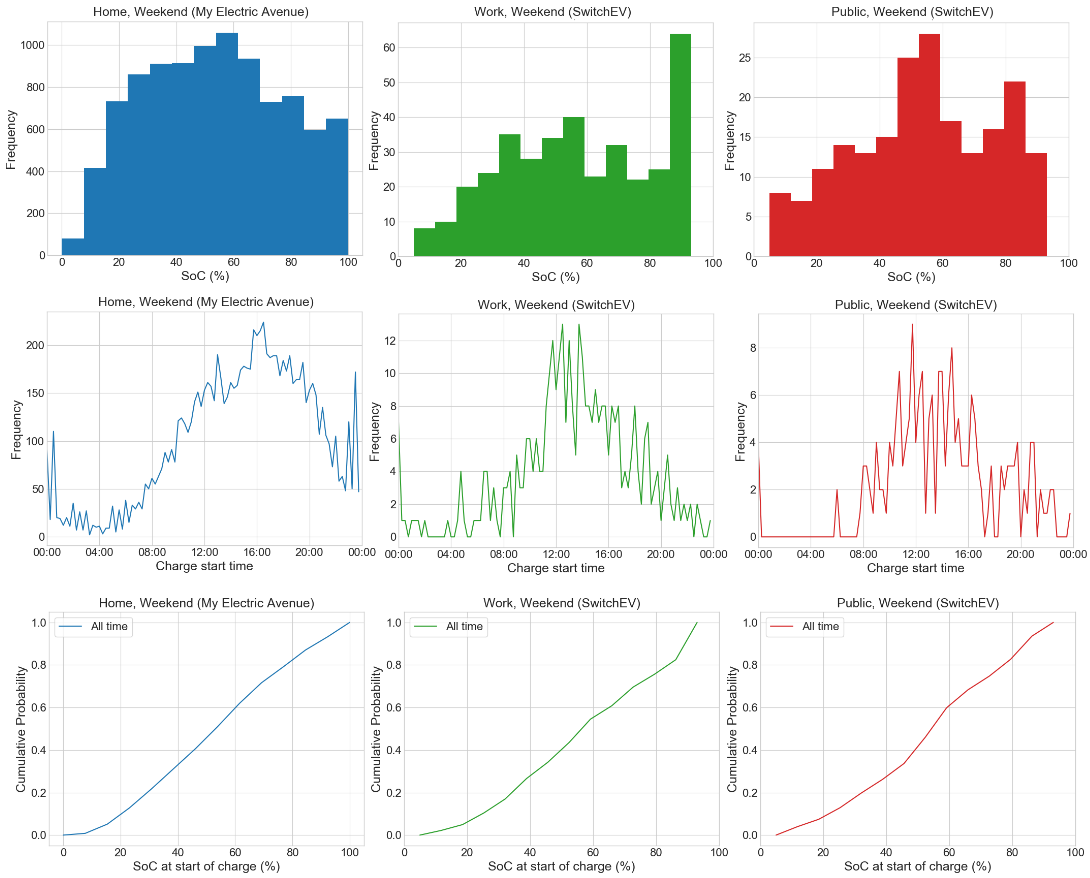

Figure A.2: Key EV trial data for weekend days (*My Electric Avenue*; *SwitchEV*) for deriving distributions of charging probability given state of charge. Top row: histograms showing state of charge at plugin, middle row: plots of charge plugin time, bottom row: cumulative distribution functions for state of charge at plugin

Beta Parameter Estimation - Method of Moments

As per the SoC modelling in Sections 3.4 and 3.5, a Beta distribution is selected to model the battery's SoC upon starting and finishing charging. The Beta distribution is characterised by two positive shape parameters α and β. The Method of Moments was used to approximate these variables from the sample data. While other methods of approximating Beta distribution shape parameters are also presented in [257], [258] and [259] both offer comparison between these methods for Beta distribution shape parameter approximation and both provide results suggesting the Method of Moments is the most accurate method of those trialled.

In any probability distribution, the first moment is equal to the mean and the second central (i.e. about the mean) moment is equal to the variance [260]. For the Beta distribution, this can be written as (A.1) for the population mean $E(X)$ and as (A.2) for the population variance $Var(X)$ [257].

$$E(X) = \frac{\alpha}{\alpha + \beta} \tag{A.1}$$

$$Var(X) = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)} \tag{A.2}$$

In the Method of Moments estimation, the sample mean $\bar{X}$ and sample variance S^2 are assumed equal to those of the population. It follows that (A.1) and (A.2) can be rearranged in terms of α and β to derive estimates for the two parameters, $\hat{\alpha}$ (A.3) and $\hat{\beta}$ (A.4) in terms of the sample mean and variance.

$$\hat{\alpha} = \bar{X}\left(\frac{\bar{X}\left(1 - \bar{X}\right)}{S^2} - 1\right) \tag{A.3}$$

$$\hat{\beta} = \left(1 - \bar{X}\right)\left(\frac{\bar{X}\left(1 - \bar{X}\right)}{S^2} - 1\right) \tag{A.4}$$

The results of this parameter estimation for home charging using the MEA dataset and work and public charging using the *SwitchEV* dataset are shown via PDFs for each case in Figure A.3. In accordance with analysis in Figures A.1 and A.2, three distributions are given for weekday data and one distribution is given for weekend data. Note that in the legends of Figure A.3, α and β are replaced with a and b respectively.

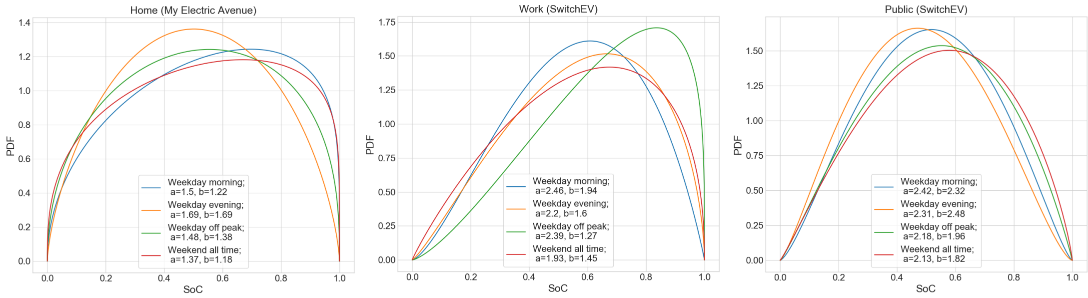

Figure A.3: Probability density functions of Beta distributions used for characterising drivers' probability of charging given battery state of charge for home, workplace and public charging

A summary of (α,β) shape parameters for the Beta distributions in Figure A.3 is presented in Table A.1.

Table A.1: Shape parameters (α,β) for Beta distributions used for characterising drivers' probability of charging given battery state of charge for home, workplace and public charging

	Home	**Work**	**Public**
Weekday morning	1.55,1.22	2.46,1.94	2.42,2.32
Weekday evening	1.69,1.69	2.20,1.60	2.31,2.48
Weekday off-peak	1.48,1.38	2.39,1.27	2.18,1.96
Weekend	1.37,1.18	1.93,1.45	2.13,1.82

Bibliography

[1] United Nations Framework Convention on Climate Change, "Paris Agreement," Tech. Rep., 2015. [Online]. Available: https://bit.ly/2EVSoXT

[2] United States Climate Alliance, "States United for Climate Action," 2018. [Online]. Available: usclimatealliance.org/

[3] S. Sengupta, M. Eddy, C. Buckley, and A. J. Rubin, "As Trump Exits Paris Agreement, Other Nations Are Defiant," 2017. [Online]. Available: https://nyti.ms/2Mckp4n

[4] Reuters, "France, Italy, Germany defend Paris Accord, say cannot be renegotiated," 2017. [Online]. Available: https://reut.rs/2J0GIYT

[5] European Court of Auditors, "The EU's response to the "dieselgate" scandal," Tech. Rep. February, 2019. [Online]. Available: https://bit.ly/2Sl0tkk

[6] World Health Organization, "9 out of 10 people worldwide breathe polluted air, but more countries are taking action," 2018. [Online]. Available: http://bit.ly/2mgSVzW

[7] ——, "Health and Sustainable Development: Air Pollution," 2017. [Online]. Available: http://bit.ly/32nPJ5y

[8] Department for Environment Food & Rural Affairs and Department for Transport, "UK plan for tackling roadside nitrogen dioxide concentrations," Tech. Rep., 2017. [Online]. Available: https://bit.ly/2tkxH53

[9] Gouvernement Republique Francais [French Government], "Climate Plan," 2017. [Online]. Available: https://bit.ly/2USyRk2

[10] J. Staufenberg, "Norway to 'completely ban petrol powered cars by 2025'," 2016. [Online]. Available: http://bit.ly/2B9TlMB

[11] Scottish Government, "A Nation With Ambition - The Government's Programme for Scotland 2017-18," Tech. Rep., 2017.

[12] E. Burke-Kennedy, "Ireland 2040: €22bn to turn State into low-carbon economy," 2018. [Online]. Available: https://bit.ly/2pgYoYS

[13] Reuters, "Denmark embraces electric car revolution with petrol and diesel ban plan," 2018. [Online]. Available: https://reut.rs/2QqLCiK

[14] Rijksoverheid, "Vertrouwen in de toekomst [Trust in the future]," Tech. Rep., 2017.

[15] Department for Transport, "The Road to Zero," Tech. Rep. July, 2018. [Online]. Available: http://bit.ly/2mJqfje

[16] IPCC, "Summary for Policymakers - Global warming of 1.5°C, an IPCC special report," Tech. Rep., 2018. [Online]. Available: https://www.ipcc.ch/2019/

[17] Committee on Climate Change, "Net Zero: The UK's contribution to stopping global warming," Tech. Rep. May, 2019. [Online]. Available: https://bit.ly/2LS8gkC

[18] BBC, "Blue Planet II," 2018. [Online]. Available: bbc.co.uk/programmes/p04tjbtx

[19] S. Rodgers, "Labour conference commits party to 2030 net-zero carbon target," 2019. [Online]. Available: https://bit.ly/2OHvg7P

[20] International Energy Agency, "CO2 Emissions Statistics," 2019. [Online]. Available: http://bit.ly/2l2mK7f

[21] RAC Foundation, "Spaced Out: Perspectives on parking policy," 2012. [Online]. Available: https://goo.gl/AfPRDD

[22] SP Energy Networks, "Connecting Electric Vehicles: Driving the way to a more sustainable future," Tech. Rep., 2018. [Online]. Available: https://bit.ly/31ngzds

[23] Ofgem, "Future Insight Series: Implications of the transition to Electric Vehicles," Tech. Rep., 2018. [Online]. Available: https://bit.ly/2KjVM4I

[24] UK Parliament, "Electric vehicles: driving the transition: Government Response to the Committee's Fourteenth Report of Session 2017-19," 2019. [Online]. Available: https://bit.ly/2OHChqQ

[25] Committee on Climate Change, "Plugging the gap: What next for Britain's EV public charging network?" 2018. [Online]. Available: https://bit.ly/2CDRS3V

[26] Department for Transport, "Public experiences of and attitudes towards parking," 2008. [Online]. Available: https://goo.gl/PQo7qX

[27] National Records of Scotland, "Estimates of Households and Dwellings in Scotland, 2016," Tech. Rep., 2017. [Online]. Available: https://goo.gl/uX7PJc

[28] Char.gy, "Lamppost electric vehicle charging for everyone," 2019. [Online]. Available: https://char.gy/

[29] National Grid, "Future Energy Scenarios 2019," Tech. Rep., 2019. [Online]. Available: http://fes.nationalgrid.com/

[30] M. Guarnieri, "Looking back to electric cars," *3rd Region-8 IEEE HISTory of Electro - Technology CONference: The Origins of Electrotechnologies, HISTELCON 2012 - Conference Proceedings*, pp. 1–6, 2012.

[31] Volkswagen, "ID.3," 2019. [Online]. Available: https://bit.ly/32eAnAv

[32] IEA, "Global EV Outlook 2019," Paris, Tech. Rep., 2019. [Online]. Available: https://bit.ly/2MwfSuV

[33] Tesla, "Model 3," 2019. [Online]. Available: http://bit.ly/2WhRK3y

[34] CAMMSYS, "CEVO Electric Vehicle," 2019. [Online]. Available: https://bit.ly/34iYxd6

[35] Vauxhall, "The All-New Electric Corsa-E," 2019. [Online]. Available: https://bit.ly/2RJNp6G

[36] Hyundai, "Kona Electric," 2019. [Online]. Available: http://bit.ly/2K2dDO3

[37] smart UK, "Smart EQ fortwo," 2019. [Online]. Available: https://bit.ly/36xYsnG

[38] United States Environmental Protection Agency, "Data on Cars used for Testing Fuel Economy," 2019. [Online]. Available: https://goo.gl/jwrFQm

[39] Zap-Map, "Charging Point Statistics 2019," 2019. [Online]. Available: https://goo.gl/xZ45CH

[40] Zap-Map, "Public Charging Networks," 2019. [Online]. Available: https://goo.gl/sX6mYr

[41] UK Data Service, "UK National Travel Survey 2002-2016," 2019. [Online]. Available: https://goo.gl/LgtfDd

[42] Ofgem, "The GB electricity transmission network." [Online]. Available: https://bit.ly/2ruOXGo

[43] Parliamentary Office of Science & Technology, "UK electricity networks," 2001. [Online]. Available: https://bit.ly/2qDJxJr

[44] Ofgem, "Distribution Network Operators." [Online]. Available: https://bit.ly/2pRRKsP

[45] J. Dowell, S. Weiss, D. Hill, and D. Infield, "Short-term spatio-temporal prediction of wind speed and direction," *Wind Energy*, vol. 17, pp. 1945–1955, 2014.

[46] Energy Systems Catapult, "Bristol Energy becomes first UK supplier to trial 'heat as a service'," 2019. [Online]. Available: https://bit.ly/2takP40

[47] P. Tielens and D. Van Hertem, "The relevance of inertia in power systems," *Renewable and Sustainable Energy Reviews*, vol. 55, no. 2016, pp. 999–1009, 2016. [Online]. Available: https://doi.org/10.1016/j.rser.2015.11.016

[48] M. Nedd, K. Bell, and C. Booth, "Containing Loss Risk in a Low Inertia Gb Power System," *Proceedings - 2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe, EEEIC/I and CPS Europe 2018*, no. 1, pp. 1–6, 2018.

[49] Q. Hong, M. Nedd, S. Norris, I. Abdulhadi, M. Karimi, V. Terzija, B. Marshall, K. Bell, and C. Booth, "Fast frequency response for effective frequency control in power systems with low inertia," *The Journal of Engineering*, vol. 2019, no. 16, pp. 1696–1702, 2019. [Online]. Available: https://doi.org/10.1049/joe.2018.8599

[50] F. Teng, Y. Mu, H. Jia, J. Wu, P. Zeng, and G. Strbac, "Challenges on primary frequency control and potential solution from EVs in the future GB electricity system," *Applied Energy*, vol. 194, pp. 353–362, 2017. [Online]. Available: https://doi.org/10.1016/j.apenergy.2016.05.123

[51] University of Strathclyde (PURE), "Personal profile - James Dixon." [Online]. Available: https://pureportal.strath.ac.uk/en/persons/james-dixon

[52] US Department of Energy, "Fuel Properties Comparison," 2014. [Online]. Available: https://goo.gl/eU1bvK

[53] Nissan, "Leaf," 2017. [Online]. Available: https://goo.gl/W1byqZ

[54] US Department of Energy, "All-Electric Vehicles." [Online]. Available: https://bit.ly/2ed7xfu

[55] "ABB powers e-mobility with launch of first 150-350 kW high power car charger," 2019. [Online]. Available: https://goo.gl/z4sf98

[56] National Grid, "Forecourt Thoughts: Mass fast charging of electric vehicles," 2017. [Online]. Available: https://goo.gl/8v2T2X

[57] T. Gnann, S. Funke, N. Jakobsson, P. Plötz, F. Sprei, and A. Bennehag, "Fast charging infrastructure for electric vehicles: Today's situation and future needs," *Transportation Research Part D: Transport and Environment*, vol. 62, pp. 314–329, 2018. [Online]. Available: https://doi.org/10.1016/j.trd.2018.03.004

[58] Porsche Engineering, "New Possibilities with 800-Volt Charging," 2016. [Online]. Available: https://goo.gl/TE9ohV

[59] L. Donaldson, "Making fast-charging electric vehicles a possibility," *Materials Today*, vol. 21, no. 2, pp. 105–106, 2018. [Online]. Available: https://doi.org/10.1016/j.mattod.2018.01.028

[60] N. S. Pearre, W. Kempton, R. L. Guensler, and V. V. Elango, "Electric vehicles: How much range is required for a day's driving?" *Transportation Research Part C: Emerging Technologies*, vol. 19, no. 6, pp. 1171–1184, 2011. [Online]. Available: https://doi.org/10.1016/j.trc.2010.12.010

[61] J. Axsen, K. S. Kurani, and A. Burke, "Are batteries ready for plug-in hybrid buyers?" *Transport Policy*, vol. 17, no. 3, pp. 173–182, 2010. [Online]. Available: https://doi.org/10.1016/j.tranpol.2010.01.004

[62] Z. Rezvani, J. Jansson, and J. Bodin, "Advances in consumer electric vehicle adoption research: A review and research agenda," *Transportation Research Part D: Transport and Environment*, vol. 34, pp. 122–136, 2015. [Online]. Available: https://doi.org/10.1016/j.trd.2014.10.010

[63] D. Diamond, "The impact of government incentives for hybrid-electric vehicles: Evidence from US states," *Energy Policy*, vol. 37, no. 3, pp. 972–983, 2009. [Online]. Available: https://doi.org/10.1016/j.enpol.2008.09.094

[64] O. Egbue and S. Long, "Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions," *Energy Policy*, vol. 48, no. 2012, pp. 717–729, 2012. [Online]. Available: https://doi.org/10.1016/j.enpol.2012.06.009

[65] A. Dimitropoulos, P. Rietveld, and J. N. van Ommeren, "Consumer valuation of changes in driving range: A meta-analysis," *Transportation Research Part A: Policy and Practice*, vol. 55, pp. 27–45, 2013. [Online]. Available: https://doi.org/10.1016/j.tra.2013.08.001

[66] M. Giansoldati, R. Danielis, L. Rotaris, and M. Scorrano, "The role of driving range in consumers' purchasing decision for electric cars in Italy," *Energy Policy*, vol. 165, pp. 267–274, 2018. [Online]. Available: https://doi.org/10.1016/j.energy.2018.09.095

[67] T. Franke and J. F. Krems, "What drives range preferences in electric vehicle users?" *Transport Policy*, vol. 30, pp. 56–62, 2013. [Online]. Available: https://doi.org/10.1016/j.tranpol.2013.07.005

[68] "Highway Code Rule 91," 2019. [Online]. Available: https://goo.gl/MtyWLS

[69] C. C. Rolim, G. N. Gonçalves, T. L. Farias, and Ó. Rodrigues, "Impacts of electric vehicle adoption on driver behavior and environmental performance," vol. 54, pp. 706–715, 2012. [Online]. Available: https://doi.org/10.1016/j.sbspro.2012.09.788

[70] M. Helmbrecht, C. Olaverri-Monreal, K. Bengler, R. Vilimek, and A. Keinath, "How electric vehicles affect driving behavioral patterns," *IEEE Intelligent Transportation Systems Magazine*, vol. 6, no. 3, pp. 22–32, 2014. [Online]. Available: https://doi.org/10.1109/MITS.2014.2315758

[71] Zap-Map, "Journey Planner," 2019. [Online]. Available: https://www.zap-map.com/route-planner/

[72] UK Petroleum Industry Association (UKPIA), "Statistical Review 2018," Tech. Rep., 2018. [Online]. Available: https://bit.ly/2koVXS7

[73] D. P. Tuttle and K. M. Kockelman, "Electrified Vehicle Technology Trends, Infrastructure Implications, And Cost Comparisons," *Journal of the Transportation Research Forum*, vol. 51, no. 1, pp. 35–51, 2012. [Online]. Available: https://doi.org/10.5399/osu/jtrf.51.1.2806

[74] Z. Lin and D. L. Greene, "Promoting the market for plug-in hybrid and battery electric vehicles," *Transportation Research Record*, no. 2252, pp. 49–56, 2011. [Online]. Available: https://doi.org/10.3141/2252-07

[75] Pod-Point, "Lidl Rapid Charging Stations," 2019. [Online]. Available: http://bit.ly/2YXdOh8

[76] BBC News, "Tesco and VW plan free electric car charging points," 2018. [Online]. Available: https://bbc.in/2QguHks

[77] Zap-Map, "Morrisons to install GeniePoint rapid chargers," 2019. [Online]. Available: http://bit.ly/2KAA9vP

[78] J. D. Bishop, C. J. Axon, D. Bonilla, M. Tran, D. Banister, and M. D. McCulloch, "Evaluating the impact of V2G services on the degradation of batteries in PHEV and EV," *Applied Energy*, vol. 111, pp. 206–218, 2013. [Online]. Available: https://doi.org/10.1016/j.apenergy.2013.04.094

[79] X. Tang, C. Zou, K. Yao, J. Lu, Y. Xia, and F. Gao, "Aging trajectory prediction for lithium-ion batteries via model migration and Bayesian Monte Carlo method," *Applied Energy*, vol. 254, no. May, 2019. [Online]. Available: https://doi.org/10.1016/j.apenergy.2019.113591

[80] London Economics, "The Value of Lost Load (VoLL) for Electricity in Great Britain: Final report for OFGEM and DECC," London, Tech. Rep., 2013. [Online]. Available: https://bit.ly/2PNAIVR

[81] Department for Transport, "Free Flow Vehicle Speed Statistics: Great Britain 2015," Tech. Rep., 2015. [Online]. Available: https://bit.ly/2t8DXzk

[82] M. Tabari and A. Yazdani, "An Energy Management Strategy for a DC Distribution System for Power System Integration of Plug-In Electric Vehicles," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 659–668, 2016. [Online]. Available: https://doi.org/10.1109/TSG.2015.2424323

[83] F. Marra, G. Y. Yang, C. Træ holt, E. Larsen, C. N. Rasmussen, and S. You, "Demand profile study of battery electric vehicle under different charging options," *IEEE Power and Energy Society General Meeting*, 2012. [Online]. Available: https://doi.org/10.1109/PESGM.2012.6345063

[84] M. Gjelaj, S. Hashemi, P. B. Andersen, and C. Træholt, “Grid Services Provision from Batteries within Charging Stations by using a Stochastic Planning Method of the EVs Demand Grid Services Provision from Batteries within Charging Stations by using a Stochastic Planning Method of the EVs Demand,” 2019.

[85] P. Zhang, K. Qian, C. Zhou, B. G. Stewart, and D. M. Hepburn, “A methodology for optimization of power systems demand due to electric vehicle charging load,” *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1628–1636, 2012. [Online]. Available: https://doi.org/10.1109/TPWRS.2012.2186595

[86] S. I. Vagropoulos and A. G. Bakirtzis, “Optimal bidding strategy for electric vehicle aggregators in electricity markets,” *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4031–4041, 2013. [Online]. Available: https://doi.org/10.1109/TPWRS.2013.2274673

[87] W. Kempton, V. Udo, K. Huber, K. Komara, S. Letendre, S. Baker, D. Brunner, and N. Pearre, “A Test of Vehicle-to-Grid (V2G) for Energy Storage and Frequency Regulation in the PJM System: Results from an Industry-University Research Partnership,” Tech. Rep., 2008. [Online]. Available: http://bit.ly/2kSTcsz

[88] L. R. Chen, S. L. Wu, D. T. Shieh, and T. R. Chen, “Sinusoidal-ripple-current charging strategy and optimal charging frequency study for Li-ion batteries,” *IEEE Transactions on Industrial Electronics*, vol. 60, no. 1, pp. 88–97, 2013. [Online]. Available: https://doi.org/10.1109/TIE.2012.2186106

[89] J. W. Huang, Y. H. Liu, S. C. Wang, and Z. Z. Yang, “Fuzzy-control-based five-step Li-ion battery charger,” *Proceedings of the International Conference on Power Electronics and Drive Systems*, pp. 1547–1551, 2009. [Online]. Available: https://doi.org/10.1109/PEDS.2009.5385780

[90] T. T. Vo, X. Chen, W. Shen, and A. Kapoor, “New charging strategy for lithium-ion batteries based on the integration of Taguchi method and state of

charge estimation," *Journal of Power Sources*, vol. 273, pp. 413–422, 2015. [Online]. Available: https://doi.org/10.1016/j.jpowsour.2014.09.108

[91] Y. Li, K. Li, Y. Xie, J. Liu, C. Fu, and B. Liu, "Optimized charging of lithium-ion battery for electric vehicles: adaptive multistage constant current–constant voltage charging strategy," *Renewable Energy*, vol. 146, pp. 2688–2699, 2019. [Online]. Available: https://doi.org/10.1016/j.renene.2019.08.077

[92] Tesla, "Model S," 2019. [Online]. Available: https://goo.gl/zKF5c7

[93] BP Chargemaster, "BP confirms rollout of 150kW chargers on BP Forecourts," 2019. [Online]. Available: http://bit.ly/2En53Wp

[94] Fastned, "Press release: Fastned opens its first 350kW-ready fast charging station in the United Kingdom," 2019. [Online]. Available: http://bit.ly/30yohlk

[95] Ionity, "Our Network," 2019. [Online]. Available: https://ionity.eu/

[96] Audi, "E-Tron - Charging," 2019. [Online]. Available: http://bit.ly/2VT0g9I

[97] Porsche, "Mission E," 2018. [Online]. Available: http://bit.ly/2w9gpJ7

[98] Connected Kerb, "Low Impact EV Charging," 2019. [Online]. Available: http://bit.ly/2w9iaG5

[99] Shell, "Shell installs UK's first 150 kW high-powered electric vehicle charger on a forecourt," 2019. [Online]. Available: http://bit.ly/2MRLOt9

[100] Electricity North West Limited, "NIA ENWL022 Reflect Uncertainties Around E-vehicle Charging To Optimise Network Forecasting Progress Report," Tech. Rep., 2019. [Online]. Available: https://bit.ly/33Q5PVQ

[101] Energy Systems Catapult, "Preparing UK Electricity Networks for Electric Vehicles Report," Tech. Rep., 2018. [Online]. Available: https://bit.ly/362Lb6f

[102] F. He, D. Wu, Y. Yin, and Y. Guan, "Optimal deployment of public charging stations for plug-in hybrid electric vehicles," *Transportation Research Part*

B: Methodological, vol. 47, no. 2013, pp. 87–101, 2013. [Online]. Available: https://doi.org/10.1016/j.trb.2012.09.007

[103] P. Jochem, C. Brendel, M. Reuter-Oppermann, W. Fichtner, and S. Nickel, "Optimizing the allocation of fast charging infrastructure along the German autobahn," *Journal of Business Economics*, vol. 86, no. 5, pp. 513–535, 2016. [Online]. Available: https://doi.org/10.1007/s11573-015-0781-5

[104] G. Wang, Z. Xu, F. Wen, and K. P. Wong, "Traffic-constrained multiobjective planning of electric-vehicle charging stations," *IEEE Transactions on Power Delivery*, vol. 28, no. 4, pp. 2363–2372, 2013. [Online]. Available: https://doi.org/10.1109/TPWRD.2013.2269142

[105] W. Yao, J. Zhao, F. Wen, Z. Dong, Y. Xue, Y. Xu, and K. Meng, "A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems," *IEEE Transactions on Power Systems*, vol. 29, no. 4, pp. 1811–1821, 2014. [Online]. Available: https://doi.org/10.1109/TPWRS.2013.2296615

[106] Y. Xiang, J. Liu, R. Li, F. Li, C. Gu, and S. Tang, "Economic planning of electric vehicle charging stations considering traffic constraints and load profile templates," *Applied Energy*, vol. 178, pp. 647–659, 2016. [Online]. Available: https://doi.org/10.1016/j.apenergy.2016.06.021

[107] M. Wen, G. Laporte, O. B. Madsen, A. V. Nørrelund, and A. Olsen, "Locating replenishment stations for electric vehicles: Application to Danish traffic data," *Journal of the Operational Research Society*, vol. 65, no. 10, pp. 1555–1561, 2014. [Online]. Available: https://doi.org/10.1057/jors.2013.100

[108] S. Guo and H. Zhao, "Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective," *Applied Energy*, vol. 158, pp. 390–402, 2015. [Online]. Available: https://doi.org/10.1016/j.apenergy.2015.08.082

[109] S. Bae and A. Kwasinski, “Spatial and Temporal Model of Electric Vehicle Charging Demand,” *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 394–403, 2012. [Online]. Available: https://doi.org/10.1109/TSG.2011.2159278

[110] M. M. Vazifeh, H. Zhang, P. Santi, and C. Ratti, “Optimizing the deployment of electric vehicle charging stations using pervasive mobility data,” *Transportation Research Part A: Policy and Practice*, vol. 121, pp. 75–91, 2015. [Online]. Available: https://doi.org/10.1016/j.tra.2019.01.002

[111] Ofcom, “The Communications Market 2018: Interactive report,” 2018. [Online]. Available: http://bit.ly/2R09r2B

[112] Google, “Popular times, wait times and visit duration.” [Online]. Available: https://goo.gl/rx3Lm2

[113] Deloitte, “Mobile Consumer Survey,” 2016. [Online]. Available: https://goo.gl/CHJNFr

[114] ComScore, “The 2017 U.S. Mobile App Report.” [Online]. Available: https://goo.gl/Bfw3UW

[115] M. Etezadi-Amoli, K. Choma, and J. Stefani, “Rapid-charge electric-vehicle stations,” *IEEE Transactions on Power Delivery*, vol. 25, no. 3, pp. 1883–1887, 2010. [Online]. Available: https://doi.org/10.1109/TPWRD.2010.2047874

[116] RAC Foundation/Deloitte, “UK Fuel Market Review,” 2013. [Online]. Available: https://goo.gl/twk6ge

[117] R. B. Cooper, “Imbedded-Markov-Chain Queueing Models,” in *Introduction to Queueing Theory*, 2nd ed. New York: Elsevier Ltd, 1981, ch. 5, pp. 176–280.

[118] Z. Zhou and T. Lin, “Spatial and temporal model for electric vehicle rapid charging demand,” *2012 IEEE Vehicle Power and Propulsion Conference, VPPC 2012*, pp. 345–348, 2012. [Online]. Available: https://doi.org/10.1109/VPPC.2012.6422675

[119] RAC Foundation, “Plug-in grant eligible vehicles licensed.” [Online]. Available: https://goo.gl/ZnR1fZ

[120] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Transactions on Power Systems*, vol. 26, no. 2, pp. 802–810, 2011. [Online]. Available: https://doi.org/10.1109/TPWRS.2010.2057456

[121] F. Yi and F. Li, "An exploration of a probabilistic model for electric vehicles residential demand profile modeling," *IEEE Power and Energy Society General Meeting*, 2012. [Online]. Available: https://doi.org/10.1109/PESGM.2012.6345721

[122] SP Energy Networks, "Flexible Networks." [Online]. Available: https://goo.gl/PyGyH7

[123] R. Mehta, D. Srinivasan, A. M. Khambadkone, J. Yang, and A. Trivedi, "Smart Charging Strategies for Optimal Integration of Plug-in Electric Vehicles within Existing Distribution System Infrastructure," *IEEE Transactions on Smart Grid*, vol. 9, no. 1, pp. 299–312, 2016. [Online]. Available: https://doi.org/10.1109/TSG.2016.2550559

[124] C. Hutson, G. K. Venayagamoorthy, and K. A. Corzine, "Intelligent scheduling of hybrid and electric vehicle storage capacity in a parking lot for profit maximization in grid power transactions," *IEEE Energy 2030 Conference*, 2008. [Online]. Available: https://doi.org/10.1109/ENERGY.2008.4781051

[125] H. Nguyen, C. Zhang, and J. Zhang, "Dynamic Demand Control of Electric Vehicles to Support Power Grid with High Penetration Level of Renewable Energy," *IEEE Transactions on Transportation Electrification*, vol. 2, no. 1, pp. 66–75, 2016. [Online]. Available: https://doi.org/10.1109/TTE.2016.2519821

[126] T. Ma, A. Mohamed, and O. Mohammed, "Optimal charging of plug-in electric vehicles for a car park infrastructure," *IEEE Transactions on Industry Applications*, vol. 50, no. 4, pp. 2323–2330, 2012. [Online]. Available: https://doi.org/10.1109/IAS.2012.6374035

[127] L. Mokgonyana, K. Smith, and S. Galloway, "Reconfigurable Low Voltage Direct Current Charging Networks for Plug-in Electric Vehicles," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5458–5467, 2018. [Online]. Available: https://doi.org/10.1109/TSG.2018.2883518

[128] C. P. Mediwaththe and D. B. Smith, "Game-Theoretic Electric Vehicle Charging Management Resilient to Non-Ideal User Behavior," *IEEE Transactions on Intelligent Transportation Systems*, 2018. [Online]. Available: https://doi.org/10.1109/TITS.2017.2784418

[129] A. R. Sparacino, S. Member, B. M. Grainger, S. Member, R. J. Kerestes, S. Member, and G. F. Reed, "Design and Simulation of a DC Electric Vehicle Charging Station Connected to a MVDC Infrastructure," in *IEEE Energy Conversion Congress and Exposition (ECCE)*, 2012. [Online]. Available: https://doi.org/10.1109/ECCE.2012.6342685

[130] Newcastle University School of Engineering, "SwitchEV," 2013. [Online]. Available: https://bit.ly/2EUw7g0

[131] E. M. Carter and H. W. Potts, "Predicting length of stay from an electronic patient record system: A primary total knee replacement example," *BMC Medical Informatics and Decision Making*, vol. 14, no. 1, pp. 1–13, 2014. [Online]. Available: https://doi.org/10.1186/1472-6947-14-26

[132] Leisure DB, "State of the UK Fitness Industry." [Online]. Available: https://goo.gl/CoJZRa

[133] Intu Braehead, "Corporate Strategy Overview." [Online]. Available: https://goo.gl/rviMoG

[134] Department for Business Energy & Industrial Strategy, "Gas and electricity prices in the non-domestic sector," 2018. [Online]. Available: https://goo.gl/giC9QQ

[135] Department for Transport, "The Road to Zero," p. 82, 2018. [Online]. Available: https://goo.gl/KZAto2

[136] G. A. Putrus, P. Suwanapingkarl, D. Johnston, E. C. Bentley, and M. Narayana, "Impact of electric vehicles on power distribution networks," *5th IEEE Vehicle Power and Propulsion Conference, VPPC '09*, pp. 827–831, 2009. [Online]. Available: https://doi.org/10.1109/VPPC.2009.5289760

[137] S. Shao, M. Pipattanasomporn, and S. Rahman, "Challenges of PHEV penetration to the residential distribution network," *2009 IEEE Power and Energy Society General Meeting, PES '09*, pp. 1–8, 2009. [Online]. Available: https://doi.org/10.1109/PES.2009.5275806

[138] K. Clement, E. Haesen, and J. Driesen, "Stochastic analysis of the impact of plug-in hybrid electric vehicles on the distribution grid," vol. 25, no. 1, pp. 160–160, 2009. [Online]. Available: https://doi.org/10.1049/cp.2009.0590

[139] L. Pieltain Fernández, T. Gómez San Román, R. Cossent, C. Mateo Domingo, and P. Frías, "Assessment of the impact of plug-in electric vehicles on distribution networks," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 206–213, 2011. [Online]. Available: https://doi.org/10.1109/TPWRS.2010.2049133

[140] P. Richardson, D. Flynn, and A. Keane, "Impact assessment of varying penetrations of electric vehicles on low voltage distribution systems," *IEEE PES General Meeting, PES 2010*, pp. 1–6, 2010. [Online]. Available: https://doi.org/10.1109/PES.2010.5589940

[141] O. Sundström and C. Binding, "Flexible charging optimization for electric vehicles considering distribution grid constraints," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 26–37, 2012. [Online]. Available: https://doi.org/10.1109/TSG.2011.2168431

[142] R. C. Leou, C. L. Su, and C. N. Lu, "Stochastic analyses of electric vehicle charging impacts on distribution network," *IEEE Transactions on Power Systems*, vol. 29, no. 3, pp. 1055–1063, 2014. [Online]. Available: https://doi.org/10.1109/TPWRS.2013.2291556

[143] J. Dunckley and G. Tal, "Plug-In Electric Vehicle Multi-State Market and Charging Survey," Electric Power Research Institute, Palo Alto, CA, Tech. Rep.

[144] S. Huang and D. Infield, "The impact of domestic plug-in hybrid electric vehicles on power distribution system loads," *2010 International Conference on Power System Technology: Technological Innovations Making Power Grid Smarter, POWERCON2010*, pp. 1–7, 2010. [Online]. Available: https://doi.org/10.1109/POWERCON.2010.5666513

[145] S. Shafiee, M. Fotuhi-Firuzabad, and M. Rastegar, "Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems," *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp. 1351–1360, 2013. [Online]. Available: https://doi.org/10.1109/TSG.2013.2251483

[146] Y. Mu, J. Wu, N. Jenkins, H. Jia, and C. Wang, "A Spatial-Temporal model for grid impact analysis of plug-in electric vehicles," *Applied Energy*, vol. 114, pp. 456–465, 2014. [Online]. Available: https://doi.org/10.1016/j.apenergy.2013.10.006

[147] E. Veldman and R. A. Verzijlbergh, "Distribution grid impacts of smart electric vehicle charging from different perspectives," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 333–342, 2015. [Online]. Available: https://doi.org/10.1109/TSG.2014.2355494

[148] A. Lojowska, D. Kurowicka, G. Papaefthymiou, and L. Van Der Sluis, "Stochastic Modeling of Power Demand due to EVs Using Copula," *IEEE Transactions on Power Systems*, vol. 27, no. 4, pp. 1960–1968, 2012. [Online]. Available: https://doi.org/10.1109/TPWRS.2012.2192139

[149] J. C. Kelly, J. S. MacDonald, and G. A. Keoleian, "Time-dependent plug-in hybrid electric vehicle charging based on national driving patterns and demographics," *Applied Energy*, vol. 94, pp. 395–405, 2012. [Online]. Available: https://doi.org/10.1016/j.apenergy.2012.02.001

[150] E. Xydas, C. Marmaras, L. M. Cipcigan, N. Jenkins, S. Carroll, and M. Barker, "A data-driven approach for characterising the charging demand of electric

vehicles: A UK case study," *Applied Energy*, vol. 162, pp. 763–771, 2016. [Online]. Available: https://doi.org/10.1016/j.apenergy.2015.10.151

[151] M. Neaimeh, R. Wardle, A. M. Jenkins, J. Yi, G. Hill, P. F. Lyons, Y. Hübner, P. T. Blythe, and P. C. Taylor, "A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts," *Applied Energy*, vol. 157, pp. 688–698, 2015. [Online]. Available: https://doi.org/10.1016/j.apenergy.2015.01.144

[152] J. Brady and M. O'Mahony, "Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data," *Sustainable Cities and Society*, vol. 26, pp. 203–216, 2016. [Online]. Available: https://doi.org/10.1016/j.scs.2016.06.014

[153] J. Dixon, I. Elders, and K. Bell, "Electric Vehicle Charging Simulations on a Real Distribution Network using Real Trial Data," in *2019 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific)*, Seogwipo-si, Korea (South), 2019. [Online]. Available: https://doi.org/10.1109/ITEC-AP.2019.8903719

[154] P. Papadopoulos, S. Skarvelis-Kazakos, I. Grau, L. Cipcigan, and N. Jenkins, "Electric vehicles' impact on British distribution networks," *IET Electrical Systems in Transportation*, vol. 2, no. 3, p. 91, 2012. [Online]. Available: https://doi.org/10.1049/iet-est.2011.0023

[155] K. P. Schneider, B. A. Mather, B. C. Pal, C. W. Ten, G. J. Shirek, H. Zhu, J. C. Fuller, J. L. R. Pereira, L. F. Ochoa, L. R. de Araujo, R. C. Dugan, S. Matthias, S. Paudyal, T. E. McDermott, and W. Kersting, "Analytic Considerations and Design Basis for the IEEE Distribution Test Feeders," *IEEE Transactions on Power Systems*, vol. PP, no. 99, pp. 1–1, 2017.

[156] F. McLoughlin, A. Duffy, and M. Conlon, "Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An

Irish case study," *Energy and Buildings*, vol. 48, no. July 2009, pp. 240–248, 2012. [Online]. Available: https://doi.org/10.1016/j.enbuild.2012.01.037

[157] F. Haldi and D. Robinson, "The impact of occupants' behaviour on building energy demand," *Journal of Building Performance Simulation*, vol. 4, no. 4, pp. 323–338, 2011. [Online]. Available: https://doi.org/10.1080/19401493.2011.558213

[158] Y. G. Yohanis, J. D. Mondol, A. Wright, and B. Norton, "Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use," *Energy and Buildings*, vol. 40, no. 6, pp. 1053–1059, 2008. [Online]. Available: https://doi.org/10.1016/j.enbuild.2007.09.001

[159] D. Stead, "Relationships between land use, socioeconomic factors, and travel patterns in Britain," *Environment and Planning B: Planning and Design*, vol. 28, no. 4, pp. 499–528, 2001. [Online]. Available: https://doi.org/10.1068/b2677

[160] B. Friedman, S. P. Gordon, and J. B. Peers, "Effect of Neotraditional Neighborhood Design on Travel Characteristics," *Transportation Research Record*, no. 1466, pp. 63–70, 1994. [Online]. Available: http://trid.trb.org/view.aspx?id=425323

[161] S. Hanson, "The determinants of daily travel-activity patterns: Relative location and sociodemographic factors," *Urban Geography*, vol. 3, no. 3, pp. 179–202, 1982. [Online]. Available: https://doi.org/10.2747/0272-3638.3.3.179

[162] SP Energy Networks, "Network Constraint Early Warning System (NCEWS) Phase 2," 2018. [Online]. Available: https://bit.ly/35eJl22

[163] S. . S. E. Networks, "My Electric Avenue," 2015. [Online]. Available: https://goo.gl/dndDmb

[164] Geopandas Development Team, "Geopandas." [Online]. Available: geopandas.org

[165] UK Data Service, "Infuse - access 2011 and 2001 UK Census data." [Online]. Available: http://infuse.ukdataservice.ac.uk/

[166] Scottish Government, "Scottish Index of Multiple Deprivation," 2016. [Online]. Available: http://bit.ly/2LlkQtK

[167] L. Thurner, A. Scheidler, F. Schäfer, J.-H. Menke, J. Dollichon, F. Meier, S. Meinecke, and M. Braun, "pandapower - an Open Source Python Tool for Convenient Modeling, Analysis and Optimization of Electric Power Systems," *IEEE Transactions on Power Systems*, vol. (Early Acc, pp. 1–12, 2018. [Online]. Available: http://arxiv.org/abs/1709.06743

[168] National Records of Scotland, "Number of rooms, household," 2018. [Online]. Available: https://www.scotlandscensus.gov.uk/number-rooms-household

[169] ——, "Scotland's Census: Tenure of household," 2018. [Online]. Available: http://bit.ly/2LnNz14

[170] A. Capasso, W. Grattier, R. Lamedica, and A. Prudenzi, "A bottom-up approach to residential load modeling," *IEEE Transactions on Power Systems*, vol. 9, no. 2, p. 8, 1994. [Online]. Available: https://doi.org/10.1109/59.317650

[171] J. Torriti, "Price-based demand side management: Assessing the impacts of time-of-use tariffs on residential electricity demand and peak shifting in Northern Italy," *Energy*, vol. 44, no. 1, pp. 576–583, 2012. [Online]. Available: https://doi.org/10.1016/j.energy.2012.05.043

[172] R. Yao and K. Steemers, "A method of formulating energy load profile for domestic buildings in the UK," *Energy and Buildings*, vol. 37, no. 6, pp. 663–671, 2005. [Online]. Available: https://doi.org/10.1016/j.enbuild.2004.09.007

[173] G. Flett and N. Kelly, "An occupant-differentiated, higher-order Markov Chain method for prediction of domestic occupancy," *Energy and Buildings*, vol. 125, pp. 219–230, 2016. [Online]. Available: https://doi.org/10.1016/j.enbuild.2016.05.015

[174] ——, "A disaggregated, probabilistic, high resolution method for assessment of domestic occupancy and electrical demand," *Energy and Buildings*, vol. 140, pp. 171–187, 2017. [Online]. Available: https://doi.org/10.1016/j.enbuild.2017.01.069

[175] Centre for Time Use Research, "United Kingdom Time Use Survey, 2014-2015." [Online]. Available: https://goo.gl/C6pMF6

[176] I. Richardson, M. Thomson, and D. Infield, "A high-resolution domestic building occupancy model for energy demand simulations," *Energy and Buildings*, vol. 40, no. 8, pp. 1560–1566, 2008. [Online]. Available: https://doi.org/10.1016/j.enbuild.2008.02.006

[177] J. Widén, A. M. Nilsson, and E. Wäckelgård, "A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand," *Energy and Buildings*, vol. 41, no. 10, pp. 1001–1012, 2009. [Online]. Available: https://doi.org/10.1016/j.enbuild.2009.05.002

[178] Department of Energy & Climate Change, "Household Electricity Survey," 2014. [Online]. Available: https://goo.gl/ajtK7j

[179] U. Wilke, "Probabilistic Bottom-up Modelling of Occupancy and Activities to Predict Electricity Demand in Residential Buildings," Ph.D. dissertation, École Polytechnique Fédérale De Lausanne, 2013. [Online]. Available: http://infoscience.epfl.ch/record/183853/files/EPFL_TH5673.pdf

[180] G. Flett, "Modelling and Analysis of Energy Demand Variation and Uncertainty in Small-Scale Domestic Energy Systems," Ph.D. dissertation, 2017. [Online]. Available: https://bit.ly/2Yqbcby

[181] J. D. Cross and R. Hartshorn, "My Electric Avenue : Integrating electric vehicles into the electrical networks," in *6th Hybrid and Electric Vehicles Conference (HEVC 2016)*, 2016, pp. 1–6. [Online]. Available: https://goo.gl/R8rZXr

[182] EA Technology, "An Assessment of Esprit Integration," Tech. Rep. June, 2015. [Online]. Available: http://bit.ly/2OSUsdw

[183] J. Quirós-tortós and B. Lees, "A statistical analysis of EV charging behavior in the UK," in *IEEE PES Innovative Smart Grid Technologies Latin America*

(ISGT LATAM), 2015. [Online]. Available: https://doi.org/10.1109/ISGT-LA.2015.7381196

[184] A. Ballanti, F. Pilo, A. Navarro-Espinosa, and L. F. Ochoa, "Assessing the benefits of PV var absorption on the hosting capacity of LV feeders," *2013 4th IEEE/PES Innovative Smart Grid Technologies Europe, ISGT Europe 2013*, pp. 1–5, 2013. [Online]. Available: https://doi.org/10.1109/ISGTEurope.2013.6695423

[185] HM Government Secretary of State, "Electricity safety, quality and continuity regulations 2002," 2002. [Online]. Available: https://bit.ly/2YUFZ1Z

[186] Western Power Distribution, "Summary of the findings of the Electric Nation smart charging trial," 2019. [Online]. Available: http://bit.ly/2l8499W

[187] EV One Stop, "Wallpod EV charging unit | Type 1 | 16/32 Amp (3.6/7.2kW)." [Online]. Available: https://bit.ly/2Mh1T9O

[188] Department of Energy & Climate Change, "The impact of changing energy use patterns in buildings on peak electricity demand in the UK," Tech. Rep., 2008. [Online]. Available: https://bit.ly/35umlfT

[189] Element Energy and Department of Energy & Climate Change, "Correlation of Consumption with Low Carbon Technologies," Tech. Rep., 2014. [Online]. Available: https://bit.ly/2lQ5Fxb

[190] Department of Energy & Climate Change, "Powering the Nation 2," Tech. Rep., 2014. [Online]. Available: http://bit.ly/2KVWlAW

[191] HM Government and Department for Transport, "Electric Vehicle Smart Charging," Tech. Rep. July, 2019. [Online]. Available: http://bit.ly/2Z3vX1Z

[192] S. Deilami, A. S. Masoum, P. S. Moses, and M. A. S. Masoum, "Real-Time Coordination of Plug-In Electric Vehicle Charging in Smart Grids to Minimize Power Losses and Improve Voltage Profile," *IEEE Transactions on Smart Grid*, vol. 2, no. 3, pp. 456–467, 2011. [Online]. Available: https://doi.org/10.1111/j.1939-0025.1959.tb00208.x

[193] M. A. Ortega-Vazquez, F. Bouffard, and V. Silva, "Electric vehicle aggregator/system operator coordination for charging scheduling and services procurement," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 1806–1815, 2013. [Online]. Available: https://doi.org/10.1109/TPWRS.2012.2221750

[194] M. Alonso, H. Amaris, J. G. Germain, and J. M. Galan, "Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms," *Energies*, vol. 7, no. 4, pp. 2449–2475, 2014. [Online]. Available: https://doi.org/10.3390/en7042449

[195] J. De Hoog, T. Alpcan, M. Brazil, D. A. Thomas, and I. Mareels, "Optimal charging of electric vehicles taking distribution network constraints into account," *IEEE Transactions on Power Systems*, vol. 30, no. 1, pp. 365–375, 2015. [Online]. Available: https://doi.org/10.1109/TPWRS.2014.2318293

[196] L. Gan, U. Topcu, and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 940–951, 2013. [Online]. Available: https://doi.org/10.1109/TPWRS.2012.2210288

[197] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1095–1105, 2012. [Online]. Available: https://doi.org/10.1109/TSG.2011.2173507

[198] C. Jin, J. Tang, and P. Ghosh, "Optimizing electric vehicle charging: A customer's perspective," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 7, pp. 2919–2927, 2013. [Online]. Available: https://doi.org/10.1109/TVT.2013.2251023

[199] E. Sortomme and M. A. El-Sharkawi, "Optimal scheduling of vehicle-to-grid energy and ancillary services," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 351–359, 2012. [Online]. Available: https://doi.org/10.1109/TSG.2011.2164099

[200] X. Hu, Y. Zou, and Y. Yang, "Greener plug-in hybrid electric vehicles incorporating renewable energy and rapid system optimization," *Energy*, vol.

111, pp. 971–980, 2016. [Online]. Available: https://doi.org/10.1016/j.energy.2016.06.037

[201] M. Honarmand, A. Zakariazadeh, and S. Jadid, "Integrated scheduling of renewable generation and electric vehicles parking lot in a smart microgrid," *Energy Conversion and Management*, vol. 86, pp. 745–755, 2014. [Online]. Available: https://doi.org/10.1016/j.enconman.2014.06.044

[202] W. P. Schill and C. Gerbaulet, "Power system impacts of electric vehicles in Germany: Charging with coal or renewables?" *Applied Energy*, vol. 156, no. 2015, pp. 185–196, 2015. [Online]. Available: https://doi.org/10.1016/j.apenergy.2015.07.012

[203] A. Zakariazadeh, S. Jadid, and P. Siano, "Integrated operation of electric vehicles and renewable generation in a smart distribution system," *Energy Conversion and Management*, vol. 89, pp. 99–110, 2015. [Online]. Available: https://doi.org/10.1016/j.enconman.2014.09.062

[204] C. Jin, X. Sheng, and P. Ghosh, "Optimized electric vehicle charging with intermittent renewable energy sources," *IEEE Journal on Selected Topics in Signal Processing*, vol. 8, no. 6, pp. 1063–1072, 2014. [Online]. Available: https://doi.org/10.1109/JSTSP.2014.2336624

[205] T. Zhang, W. Chen, Z. Han, and Z. Cao, "Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 6, pp. 2600–2612, 2014. [Online]. Available: https://doi.org/10.1109/TVT.2013.2295591

[206] D. Dallinger, S. Gerda, and M. Wietschel, "Integration of intermittent renewable power supply using grid-connected vehicles - A 2030 case study for California and Germany," *Applied Energy*, vol. 104, pp. 666–682, 2013. [Online]. Available: https://doi.org/10.1016/j.apenergy.2012.10.065

[207] C. K. Ekman, "On the synergy between large electric vehicle fleet and high wind penetration - An analysis of the Danish case," *Renewable Energy*, vol. 36, no. 2, pp. 546–553, 2011. [Online]. Available: https://doi.org/10.1016/j.renene.2010.08.001

[208] S. Bellekom, R. Benders, S. Pelgröm, and H. Moll, "Electric cars and wind energy: Two problems, one solution? A study to combine wind energy and electric cars in 2020 in The Netherlands," *Energy*, vol. 45, no. 1, pp. 859–866, 2012. [Online]. Available: https://doi.org/10.1016/j.energy.2012.07.003

[209] K. Jorgensen, "Technologies for electric, hybrid and hydrogen vehicles: Electricity from renewable energy sources in transport," *Utilities Policy*, vol. 16, no. 2, pp. 72–79, 2008. [Online]. Available: https://doi.org/10.1016/j.jup.2007.11.005

[210] H. Ma, F. Balthasar, N. Tait, X. Riera-Palou, and A. Harrison, "A new comparison between the life cycle greenhouse gas emissions of battery electric vehicles and internal combustion vehicles," *Energy Policy*, vol. 44, pp. 160–173, 2012. [Online]. Available: https://doi.org/10.1016/j.enpol.2012.01.034

[211] Office for Low Emission Vehicles, "Driving the Future Today - A strategy for ultra low emission vehicles in the UK," Tech. Rep., 2013. [Online]. Available: https://bit.ly/2PMggo8

[212] R. Carter, A. Cruden, D. Densley, and T. Nicklin, "Timed Charging Points for Electric Vehicles: User Behaviour and Potential Impacts to Low Voltage Networks," in *European Electric Vehicle Congress (EEVC)*, 2011.

[213] IRENA, "Innovation outlook: Smart charging for electric vehicles," International Renewable Energy Agency, Abu Dhabi, Tech. Rep., 2019.

[214] Greenflux, "Smartest in Electric Vehicle Charging," 2019. [Online]. Available: greenflux.com/

[215] Crowd-Charge, "Save money charging your electric vehicle," 2019. [Online]. Available: crowd-charge.com/

[216] National Grid, "Carbon Intensity Forecast Methodology," 2017. [Online]. Available: http://bit.ly/2mO0GOa

[217] Elexon, "Balancing Mechanism Reports Online." [Online]. Available: https://bit.ly/2qq97ku

[218] W. A. Bukhsh, A. Grothey, K. I. McKinnon, and P. A. Trodden, "Local solutions of the optimal power flow problem," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4780–4788, 2013. [Online]. Available: https://doi.org/10.1109/TPWRS.2013.2274577

[219] J. F. Franco, L. F. Ochoa, and R. Romero, "AC OPF for smart distribution networks: An efficient and robust quadratic approach," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 4613–4623, 2018.

[220] D. Hirst, "Carbon Price Floor (CPF) and the price support mechanism," Tech. Rep., 2018. [Online]. Available: https://bit.ly/2PIPQUu

[221] W. A. Bukhsh, "OATS : Optimisation and Analysis Toolbox for Power Systems," 2019. [Online]. Available: https://github.com/bukhsh/oats

[222] Clark W. Gellings, "The Concept of Demand-Side Management for Electric Utilities," *Proceedings of the IEEE*, no. 10, pp. 1468–1470, 1985. [Online]. Available: https://doi.org/10.1109/PROC.1985.13318

[223] Sohn Associates Limited, "Electricity Distribution Systems Losses: Non-Technical Overview (Report Prepared for OFGEM)," Tech. Rep., 2006. [Online]. Available: https://bit.ly/34wY87k

[224] Google, "Google Maps," 2019. [Online]. Available: https://www.google.co.uk/maps

[225] A. Moro and L. Lonza, "Electricity carbon intensity in European Member States: Impacts on GHG emissions of electric vehicles," *Transportation Research Part D: Transport and Environment*, vol. 64, no. November 2016, pp. 5–14, 2018. [Online]. Available: https://doi.org/10.1016/j.trd.2017.07.012

[226] I. Staffell, "Measuring the progress and impacts of decarbonising british electricity," *Energy Policy*, vol. 102, pp. 463 – 475, 2017. [Online]. Available: https://doi.org/10.1016/j.enpol.2016.12.037

[227] The Committee on Climate Change, "The fifth carbon budget: the next step towards a low-carbon economy," Tech. Rep., 2019. [Online]. Available: https://bit.ly/2rIuHSh

[228] National Grid, "Electricity Ten Year Statement 2018," https://bit.ly/2qs7Yc7.

[229] European Environment Agency, "Average CO2 emissions from new cars and new vans increased in 2018," 2019. [Online]. Available: http://bit.ly/2mo8iXu

[230] Transport Scotland, "Scottish Transport Statistics: No. 35 - 2016 Edition," The Scottish Government, Edinburgh, Tech. Rep., 2016. [Online]. Available: https://bit.ly/33kFi3o

[231] House of Commons Business Energy and Industrial Strategy Committee, "Electric vehicles: driving the transition (Fourteenth Report of Session 2017–19)," UK Parliament, London, Tech. Rep., 2018. [Online]. Available: https://bit.ly/38xYRZ0

[232] H. Gerard, E. I. Rivero Puente, and D. Six, "Coordination between transmission and distribution system operators in the electricity sector: A conceptual framework," *Utilities Policy*, vol. 50, pp. 40–48, 2018. [Online]. Available: https://doi.org/10.1016/j.jup.2017.09.011

[233] K. Bell and S. Gill, "Delivering a highly distributed electricity system: Technical, regulatory and policy challenges," *Energy Policy*, vol. 113, no. October 2017, pp. 765–777, 2018. [Online]. Available: https://doi.org/10.1016/j.enpol.2017.11.039

[234] C. Edmunds, S. Galloway, I. Elders, W. Bukhsh, and R. Telford, "A DSO-TSO balancing market coordination scheme for the decentralised energy future," *IET Generation, Transmission & Distribution*, 2019. [Online]. Available: https://doi.org/5C10.1049/iet-gtd.2019.0865

[235] Western Power Distribution, "SDRC-4 Trialling and demonstrating the EVA method," Tech. Rep., 2017. [Online]. Available: http://bit.ly/2r1LM8Z

[236] G. Strbac, P. Djapic, D. Pudjianto, I. Konstantelos, and R. Moreira, "Strategies for reducing losses in distribution networks," Tech. Rep., 2018. [Online]. Available: http://bit.ly/2C5n0Hf

[237] M. Castro, A. Moon, L. Elner, D. Roberts, and B. Marshall, "The value of conservation voltage reduction to electricity security of supply," *Electric Power Systems Research*, vol. 142, pp. 96–111, 2017. [Online]. Available: https://doi.org/10.1016/j.epsr.2016.09.006

[238] C. Crozier, T. Morstyn, M. Deakin, and M. McCulloch, "The case for Bi-directional charging of electric vehicles in low voltage distribution networks," *Applied Energy*, vol. 259, p. 114214, 2020. [Online]. Available: https://doi.org/10.1016/j.apenergy.2019.114214

[239] OVO Energy, "Vehicle 2 Grid Trial," 2020. [Online]. Available: https://bit.ly/3aQTEvL

[240] Octopus Energy, "Octopus Go," 2019. [Online]. Available: https://bit.ly/36q393w

[241] Bulb, "Smart Tariff," 2019. [Online]. Available: https://bit.ly/33heHUK

[242] OVO Energy, "EV Everywhere Tariff," 2019. [Online]. Available: https://bit.ly/2PNkrl9

[243] National Grid, "Wider Access to the Balancing Mechanism Roadmap," 2019. [Online]. Available: https://ngrid.com/2BSNyhN

[244] ——, "An Introduction to Project TERRE," 2019. [Online]. Available: https://bit.ly/37KT0PE

[245] ——, "Every little helps - big boost for smaller electricity providers," 2019. [Online]. Available: https://ngrid.com/2BSNyhN

[246] Department for Business Energy & Industrial Strategy, "Digest of UK Energy Statistics 2019 - Statistical Press Release," Tech. Rep., 2019. [Online]. Available: https://bit.ly/2RgFmxQ

[247] P. Emmerson, J. Anable, T. Chatterton, S. Cairns, E. Wilson, and S. Ball, "Analysing MOT vehicle licensing data and transport model data to generate insights about car use and emissions in Strathclyde," in *Scottish Transport Appplications Research*, 2016, pp. 1–15. [Online]. Available: http://www.starconference.org.uk/star/2016/Emmerson.pdf

[248] S. Cairns, J. Anable, T. Chatterton, E. Wilson, and C. Morton, "MOToring Along : The lives of cars seen through licensing and test data," Tech. Rep., 2017. [Online]. Available: https://bit.ly/2qcburh

[249] Scottish Government, "Just Transition Commission: Background Report," Edinburgh, Tech. Rep., 2019. [Online]. Available: https://bit.ly/2rPRCuL

[250] Ofgem, "Charging arrangements." [Online]. Available: https://bit.ly/2Yd5aMX

[251] Department of Energy & Climate Change, "Performance and Impact of the Feed-in Tariff Scheme: Review of Evidence," Tech. Rep., 2015. [Online]. Available: https://bit.ly/38DFvBC

[252] Office for National Statistics, "Percentage of households with cars by income group, tenure and household composition: financial year ending 2018," 2019. [Online]. Available: https://bit.ly/2LlbAnX

[253] Department for Transport UK, "Road Traffic Forecasts 2018," London, Tech. Rep., 2018. [Online]. Available: https://bit.ly/2Yb1j2K

[254] Smarter Together, "Lyon," 2019. [Online]. Available: https://bit.ly/34NmI4x

[255] Birmingham City Council, "Birmingham Mobility Action Plan White Paper," no. November, 2014.

[256] Glasgow City Council, "Avenues," 2014. [Online]. Available: https://www.glasgow.gov.uk/avenues

[257] L. J. Bain and M. Engelhardt, *Introduction-to-Probability-and-Mathematical-Statistics-Second-Edition.pdf*, 2nd ed. Brooks/Cole, 1992.

[258] R. C. Tripathi, R. C. Gupta, and J. Gurland, "Estimation of parameters in the beta binomial model," *Annals of the Institute of Statistical Mathematics*, vol. 46, no. 2, pp. 317–331, 1994. [Online]. Available: https://doi.org/10.1007/BF01720588

[259] C. E. O. Owen, "Parameter Estimation for the Beta Distribution BYU ScholarsArchive Citation," Ph.D. dissertation, Brigham Young University, 2008. [Online]. Available: http://bit.ly/2XcbPsA

[260] A. Spanos, *Probability Theory and Statistical Inference: Econometric Modeling With Observational Data*. New York: Cambridge University Press, 2009.